

# Is the IT revolution over? An asset pricing view

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## Abstract

I develop a method that puts structure on financial market data to forecast economic outcomes. I apply it to study the IT sector's transition to its long-run share in the US economy, along with its implications for future growth. Future average annual productivity growth is predicted to fall to 52bps from the 87bps recorded over 1974–2012, due to intensifying IT sector competition and decreasing returns to employing IT. My median estimate's two standard-error confidence interval indicates the transition ends between 2032 and 2038. I estimate these numbers by building an asset pricing model that endogenously links economy-wide growth to IT sector innovation governed by the sector's market valuation, and by calibrating it to match historical data on factor shares, price-dividend ratios, growth rates, and discount rates. Consistent with this link, I show empirically that the IT sector's price-dividend ratio univariately explains nearly half of the variation in future productivity growth.

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# 1 Introduction

Information technology continues to change the way firms do business. While the market valuations of star firms, like Apple and Google, make headlines, the broad economy’s continued adoption of IT drives improvements in output and productivity, leading Jorgenson, Ho and Samuels (2011) to conclude that “...information technology capital input was by far the most significant [contributor to US economic growth over the period 1995–2007].” Substantial controversy exists, however, over IT’s future bearing on US growth, perhaps arising from existing analyses’ heavy reliance on historical macroeconomic data.<sup>1</sup>

In this paper, I argue that we can learn more about IT’s future bearing by better structuring our use of forward-looking financial market data. To my knowledge, the method I develop to do this is new. While I apply it to IT because of the sector’s importance to growth and growth’s first-order implications for pension fund financial health, government indebtedness, and firm investment, it could in principle be applied to study other phenomena, such as peak oil, as well.

I begin by building an asset pricing model that endogenously links economy-wide growth to innovation in the IT sector, with an intensity governed by the sector’s market valuation.<sup>2</sup> Consistent with this link, I empirically show that the IT sector’s price-dividend ratio univariately explains nearly half of the variation in future productivity growth. I then calibrate the model’s transition paths to match historical data of factor shares, price-dividend ratios, growth rates, and discount rates. This calibrated model allows me to study the IT sector’s temporal evolution toward its long-run factor share and to estimate its future bearing on growth.

My median estimate’s two standard-error confidence interval indicates the transition ends between 2032 and 2038, approximately six decades after its 1974 inception. Future average annual productivity growth for the next twenty years is predicted to approximately fall to 52bps from the 87bps recorded over 1974–2012. This is due to both an intensifying of competition in the IT sector, which reduces the marginal benefit of it innovating, and decreasing returns in the broad economy’s employment of IT.

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<sup>1</sup>Moore (2003), Brynjolfsson and McAfee (2011), and Byrne, Oliner and Sichel (2013) are optimistic, whereas Cowen (2011) and Gordon (2000, 2012, 2013) are not. Even *The Economist* held an internet debate over 4-15 June 2013 on whether technological progress is accelerating. The summary is listed here: <http://www.economist.com/debate/files/view/Techprogressartifact0.pdf>.

<sup>2</sup>I define the IT sector in Appendix B. I call the IT sector’s complement (the “non-IT” sector) the industrial sector. Regarding factor shares, IT capital—the sum of hardware, software, and communications capital—is treated as a type of capital distinct from industrial capital; the former being referred to as “IT”; the latter, simply as “capital”. Both refer to stocks of a quantity of “machines”. Hence, the IT-capital ratio, which will be prominently featured in what follows, is analogous to a capital-labor ratio, both cases being a relative intensity of factor use.

Furthermore, I make two additional predictions about the IT sector's evolution. First, the sector is more likely to reach its long-run share within the decade before the median estimate of 2035 than within the decade after: formally, the density of convergence times of when the sector's long-run share is reached is right-skewed. Because dear IT sector valuations lead to economy-wide growth and, importantly, vice versa, the model exhibits a salient equilibrium effect that hastens the transition.

Second, the model not only makes predictions about changes in growth rates, but also about changes in covariances, and thus changes in the nature of systematic risk. More specifically, the information technology sector is initially exposed to negative shocks to expected growth, but later in the transition serves as a hedge against adverse innovations to expected growth in the long run. Indeed, in the long run bad news about expected growth raises IT's possible future contribution to growth; upon impact, the sector's price-dividend ratio encodes this news and rises. More broadly, this study suggests because systematic risk is changing over time, studies of asset prices employing a particular sample period for empirical analysis might be prone to generating conclusions that are not fully representative of the secular pattern in the economy being investigated.

To elaborate on how we can use asset prices to forecast a sector's growth prospects and future relative size, consider the Gordon growth model for an economy populated by risk-neutral investors:

$$\frac{P_0^{(i)}}{D_0^{(i)}} = \frac{1}{r - g^{(i)}},$$

where  $i$  denotes the sector;  $P$ , the sector's market capitalization;  $D$ , its aggregate payout; and  $g$ , its dividend growth rate. Specify two sectors, and endow the first sector with a slower growth rate,  $g = g^{(1)} < g^{(2)} = g + \Delta$ , where  $\Delta > 0$  is a growth wedge, possibly reflecting an exceptional dividend growth rate or a growing mass of sector constituents. If this endowment were permanent, the outcome would be trivial: sector one's dividend share tends to zero and sector two dominates in the long run. An interesting analysis emerges, however, if sector two's superior growth rate is transient.

Consider now a *convergence time*  $T > 0$  when sector two's growth rate instantaneously converges to sector one's. Sector two's price-dividend ratio becomes<sup>3</sup>

$$\frac{P_0^{(2)}}{D_0^{(2)}} = \frac{1}{r - g - \Delta} \left[ 1 - \frac{e^{-(r-g-\Delta)T}}{r - g} \Delta \right]. \quad (1)$$

By estimating values of  $r$ ,  $g$ , and  $\Delta$ , and by observing sector two's price-dividend ratio at a

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<sup>3</sup>Equation (1) solves  $\int_0^T D_0^{(2)} e^{(g+\Delta)s} e^{-rs} ds + e^{-rT} P_T^{(2)}$ , where  $P_T^{(2)} = D_T^{(2)} / (r - g) = D_0^{(2)} e^{(g+\Delta)T} / (r - g)$ . Setting either  $T$  or  $\Delta$  to zero reduces it to the Gordon growth model and to sector one's ratio.

point in time, we can back out an estimated value of  $T$ . A corollary of this exercise is that we can infer the future relative size of the sectors because both  $\Delta$  and  $T$  are now known:

$$\frac{D_T^{(2)}}{D_T^{(1)}} = \frac{D_0^{(2)}}{D_0^{(1)}} \times e^{\Delta T},$$

the current dividend ratio scaled by the temporary relative growth factor.

This stylized example illustrates the paper’s novelty in inferring a convergence time from asset prices and relating them to future shares and thus potential growth contributions in the economy. In the paper, I proceed to construct a more detailed model by introducing additional features such as stochastic growth, uncertainty and risk, investment, and sectoral interdependence. This fleshed-out model allows me to match historical paths of pertinent macroeconomic and asset market data, and then to use its structure to infer both when the IT sector’s transition ends and the associated gains to future productivity growth.

An alternative to model-building would be estimating a vector autoregression that employs present-value restrictions, like those developed in van Binsbergen and Koijen (2010). This study’s chief endogenous state variable, IT’s factor share, would pose two challenges to favoring this alternative, however. Factor shares are highly persistent processes, and the temporal behavior associated with the unfolding of a transition path would likely be a non-linear and low-frequency movement. Model-building allows me to directly model the nonstationarity and the low-frequency movement of the factor share, thereby overcoming these two challenges.

## Related literature

My paper builds on the work that relates financial market performance to shifts in the technological frontier.<sup>4</sup> Pástor and Veronesi (2006, 2009) develop models where learning about a firm’s profitability or a technology’s productivity coincides with periods of high volatility and bubble-like patterns in stock prices. Gârleanu, Panageas and Yu (2012b) study the asset pricing implications of large, infrequent technological innovations that require firm-specific investment to be adopted. Because firms are heterogeneous, firm-specific adoption is staggered across time, generating economy-wide persistence and investment-driven cycles. Moreover, their view that aggregate growth options become embedded in the economy at the start of the innovation, and then are sequentially exercised, is one shared with this paper. I take the presence of the IT sector as given, and study the financial market effects of a gradual shift in the technological frontier as the sector expands by exercising its growth options and

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<sup>4</sup>A partial list includes Jovanovic and MacDonald (1994), Greenwood and Jovanovic (1999), Hobijn and Jovanovic (2001), Cochrane (2003), Ofek and Richardson (2003), Abel and Eberly (2012), Kogan, Papanikolaou, Seru and Stoffman (2012), and Kogan, Papanikolaou and Stoffman (2013).

transitions towards its long-run factor share. By studying this gradual shift in detail, I'm able to use my model to ultimately forecast growth.

That said, my paper adds to the literature linking asset prices to aggregate growth to innovation in the economy.<sup>5</sup> The model developed here extends the work done in Romer's (1990) seminal paper, in a similar direction to the one taken by Comin and Gertler (2006). Kung and Schmid (2012) build a growth model, one that is adopted and modified here, but focus on the quantitative difference implied by assuming exogenous or endogenous growth. Indeed, because of their insightful specification of recursive preferences coupled with an endogenous persistent growth process, they show these types of model performs better in jointly matching macroeconomic and asset market data. Their insight of asset prices reflecting anticipated future growth is one shared in this paper. While their paper features R&D, an economic quantity, as the chief predictive state variable, my paper places the IT sector's price-dividend ratio, a financial market ratio, as the centerpiece. On top of this, I specifically model the R&D activity of IT firms as being subject to decreasing, and not constant, returns to scale. This specification grants the IT sector with growth options that are integral for embedding information about the sector's future size in today's sectoral market valuation.

Gârleanu, Kogan and Panageas (2012a) study a growth model of innovation in an overlapping-generations economy. They find that innovation increases the competitive pressure of existing firms, similarly to this study, and that a lack of intergenerational risk sharing introduces a new source of systematic risk in the economy, which they call displacement risk. My work differs in context and application. I explicitly model the innovation sector as the IT sector, and map all model features directly to readily available public market data and investment data. I also focus on the model's transition paths: I initialize the economy with a small IT sector and study its evolution to its larger, long-run share, triangulating the model's transition paths with macroeconomic and asset market data, and using this triangulation to forecast the potential gains to growth.

Finally, my paper fits into the large literature tying cross-sectional and time-series asset returns to production economies.<sup>6</sup> Gomes, Kogan and Yogo (2009) develop a production economy with two types of firms that links heterogeneity in output to differences in average returns. While the firms' decisions are intertwined through a common variable factor of production and the representative household's choices, they otherwise operate independently.

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<sup>5</sup>For example, Grossman and Helpman (1991), Aghion and Howitt (1992), Beaudry and Portier (2004), Beaudry and Portier (2006), Atkeson and Kehoe (2007), Acemoglu (2009), and Opp (2010).

<sup>6</sup>Contributions include Cochrane (1996), Jermann (1998), Berk, Green and Naik (1999), Gomes, Kogan and Zhang (2003), Carlson, Fisher and Giammarino (2004), Kogan (2004), Zhang (2005), Cochrane (2006), Novy-Marx (2007), Belo (2010), Gala (2010), Kaltenbrunner and Lochstoer (2010), Gourio (2012), Kogan and Papanikolaou (2013a), Kogan and Papanikolaou (2013b), and Loualiche (2013).

My model features two interdependent sectors where one sector's output is the other's input and also generates sectoral differences in average returns. Work on investment-specific shocks, originating with Greenwood, Hercowitz and Krusell (1997) and later being linked to asset prices by Papanikolaou (2011), suggests that investment-good producers load more than do consumption-good producers on investment shocks, which carry a negative price of risk, thus earning lower returns like growth firms. In my model the IT sector is analogous to an investment-good production sector, but it earns lower returns due to relatively smaller, and eventually negative, loadings on factors with positive risk prices.

I structure the paper as follows. Section 2 describes the model environment. Section 3 tests some of the model's predictions empirically. Section 4 calibrates, simulates, and analyzes the full model. Section 5 concludes.

## 2 Environment

There are two sectors: the industrial sector and the IT sector. The information technology sector houses both a production division and a research division. The industrial sector rents IT goods from the IT sector; these goods enhance the productivity of the industrial sector, and the greater the variety of goods, the greater the enhancement. Sustained demand for these goods increases the value of them and incentivizes the IT sector to create more of them. The information technology sector conducts research today in anticipation of creating new IT goods tomorrow. The created goods are subsequently rented by the industrial sector, and through this process, an endogenous component of growth emerges.

### 2.1 Information technology sector

#### Market structure and product division

The information technology sector is subject to two critical forces: cost structures and network economies.<sup>7</sup> Large fixed costs and tiny marginal costs are rarely observed in the industrial economy, but for the IT sector, they are common.<sup>8</sup> This cost structure cultivates supply-side economies of scale.

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<sup>7</sup>There are several other important forces that affect the IT sector. See Shapiro and Varian (1999) for an excellent overview.

<sup>8</sup>This is not just true for pure information goods, such as ebooks and other media, but even for physical goods such as silicon chips. Constructing a chip fabrication plant can cost several billion dollars, but producing an incremental chip only costs a few dollars. Bakos and Brynjolfsson (1999) study a strategy of bundling a large number of information goods and selling them for a fixed price, like Microsoft Office. They show empirical evidence that this strategy works better for and is used more widely by the IT sector because its marginal costs of production are low. Other industries rely on bundling less often because their marginal costs are higher, which reduces the net benefit of bundling.

The distinguishing feature of a good exhibiting network economies is that the demand for the good depends on how many other people use it.<sup>9</sup> Network economies also contribute to another effect that fosters market power: lock-in. Consider learning software. Becoming proficient with a piece of software takes time. Switching to a new piece of software is costly because you will have to relearn computing commands or functions; switching shoes from Nike to Adidas, on the other hand (foot), is trivial. At the organizational level, the effect of lock-in can potentially be huge.

These forces coalesce to endow producers of IT goods with market power, and I consequently model the sector as monopolistically competitive. There is a fixed continuum of IT firms of unit measure that comprise the IT sector. Each IT firm is of zero measure and indexed by  $f$ . Information technology goods produced by the whole sector are on a continuum of measure  $N_t$ , and are indexed by  $g$ , with  $g$  indexing a good's particular variety. Each firm monopolistically prices its good(s).<sup>10</sup> Information technology capital is notorious for depreciating quickly, so I make a further technically simplifying assumption: it depreciates fully every period.

Consider the quantity demanded,  $X_t(g)$ , which will be later explicitly modeled, for some IT good  $g \in [0, N_t]$ . The monopolist of the IT good takes  $X_t(g)$  as given and sets prices to maximize its profit, subject to a linear production function that is common to all monopolists. My assumptions imply that every monopolist sets the same price,  $P_t(g)$ , in every period (See Appendix A for the derivation):

$$P_t(g) = \mu, \text{ for every } g \text{ and } t.$$

In consequence of this result, the quantity demanded,  $X_t(g)$ , and profit earned,  $\Pi_t(g)$ , for each IT good are equal across varieties:

$$X_t(g) = X_t, \text{ for each } g \quad \text{and} \quad \Pi_t(g) = \Pi_t = (\mu - 1)X_t, \text{ for each } g.$$

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<sup>9</sup>Purchasing a word processor with the largest market share is natural, as it allows you to more easily transfer files, resolve problems online, and work on multi-authored documents. Goolsbee and Klenow (2002) examine the importance of network externalities in the diffusion of home computers. Controlling for many characteristics, they find that people are more likely to first-time buy a computer in areas where a high proportion of households already own one. Additional results suggest these patterns are unlikely to be explained by common unobserved traits or by features of the area.

<sup>10</sup>Thus, the measure of IT goods,  $N_t$ , reflects the entire sector's product line. Because any firm produces a zero-measure set of IT goods, there is no feedback from the price a single firm charges in relation to the prices charged by other firms, so the firm consequently prices its own goods independently of its other goods and of the rest of the sector. Since I focus on the IT sector as a whole, I abstract from intra-industry strategies to substantially simplify the analysis. You can think about this market structure as having the IT sector provide many differentiated products to the industrial sector; for example, the goods could be smart phones, robots, consulting services, and even applications (apps)—any product that enhances productivity.

Profitability here is kept simple: each IT good producer simply charges a markup over marginal cost, and earns the difference multiplied by the quantity demanded. Assumptions culminating to a constant markup may not be as serious as they initially may seem: estimates for the IT sector's average markup shows no discernable trend over time (see Table 5).

I introduce a parameter  $1 - \phi$  to denote the probability that an existing IT good becomes obsolete, is no longer demanded by the industrial sector, and thus has zero value. The value for any IT good,  $V_t$ , then, can be written recursively as

$$V_t = \Pi_t + \phi \mathbb{E}_t[M_{t+1}V_{t+1}],$$

where  $M_{t+1}$  is the stochastic discount factor, and  $\mathbb{E}_t[\cdot] \doteq \mathbb{E}[\cdot|\mathcal{F}_t]$  denotes the conditional expectation with respect to the filtration  $\mathcal{F}_t$  that includes all information up to time  $t$ . Because all IT goods have identical values, newly developed IT goods are expected to have the same value. Thus, information technology firms will conduct relatively more research to create new IT goods when the value of them is high.

### Research division

The information technology sector as a whole spends a lot on research and development.<sup>11</sup> The division for research is contained within the IT sector and is characterized by two conditions. First, any IT firm  $f$  in the IT sector can conduct research subject to a common, decreasing returns to scale technology, parameterized by  $\eta_s \in [0, 1)$ . Second, each firm's research independently realizes success or failure, and the existence of a stock market allows IT firms' owners to diversify away these idiosyncratic risks. Information technology firm  $f$ 's research problem is to choose its research expenditure,  $S_t(f)$ , to maximize

$$\max_{S_t(f)} \mathbb{E}_t[M_{t+1}R_{t+1}(f)] - S_t(f)$$

where revenue generated by research is  $R_{t+1}(f) = \theta_t S_t(f)^{\eta_s} V_{t+1}$ : the quantity of IT goods created,  $\theta_t S_t(f)^{\eta_s}$ , is multiplied by the value of each good,  $V_{t+1}$ . Accordingly, I define aggregate research revenue across the IT sector as

$$R_{t+1} \doteq \int_0^1 R_{t+1}(f) df$$

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<sup>11</sup>Computing and electronics, and software and internet firms constituted 35 percent of total R&D expenditure worldwide in 2011 according to Jaruzelski, Loehr and Holman (2012, p.6, Exhibit C). As a fraction of sales, research and development expenditure is also higher for IT firms on average: seven to ten percent of sales versus under two percent for industrial firms. These latter estimates are from my own calculations on Compustat data.

These assumptions jointly lead to a condition where the marginal benefit of research is equated with its marginal cost for every firm:

$$1 = \theta_t \times \eta_s S_t(f)^{\eta_s - 1} \times \mathbb{E}_t[M_{t+1}V_{t+1}], \text{ for every } f \in [0, 1]. \quad (2)$$

The left side is the marginal cost of research. The right side is the marginal benefit of research, which is interacted with a time-varying externality,  $\theta_t$ , that is taken as given by an individual firm. I interpret the externality as a measure of research productivity and give it the following form:

$$\theta_t = \bar{\theta} N_t^{1 - \eta_s - \eta_k} K_t^{\eta_k}.$$

The scale parameter  $\bar{\theta}$  adjusts the model's long-term growth rate. I specify the elasticity of new IT good development with respect to research to be  $\eta_s$ , which corresponds with its research production technology. And I index the strength of a capital reallocation friction with the parameter  $\eta_k$ . I assume  $-1 < \eta_k \leq 0$  to make the externality aid the model in generating an S-shaped diffusion curve by capturing two features:<sup>12</sup>

$$\frac{\partial \theta_t}{\partial N_t} > 0 \quad \text{and} \quad \frac{\partial \theta_t}{\partial (K_t/N_t)} < 0.$$

The left-hand derivative sets research productivity to be increasing in  $N_t$ , capturing the idea that a set of technologies with a rich set of components, like microprocessors, can be combined and recombined to produce new products. The right-hand derivative acts as a capital reallocation friction, possibly arising from it being difficult to integrate IT into myriad capital, for each integration could require an ad hoc approach, or from the accumulation of knowledge on existing capital disincentivizing the learning about novel capital, as in Atkeson and Kehoe (2007).

Each IT firm chooses to spend  $S_t(f)$  units of the final good on research, creating the quantity  $\theta_t S_t(f)^{\eta_s}$ , and the measure  $\phi N_t$  remains the following period. The law of motion for IT goods, then, takes this form:

$$N_{t+1} = \phi N_t + \int_0^1 \theta_t S_t(f)^{\eta_s} df = \phi N_t + \theta_t S_t^{\eta_s}, \text{ with } N_0 > 0. \quad (3)$$

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<sup>12</sup>A S-shaped diffusion curve has three temporal states: initially, the adoption of the new technology is slow because its efficacy could be unclear; later, once the new technology becomes better understood, the pace of adoption rapidly picks up; finally, as the economy becomes saturated with the new technology, its rate of adoption slows and plateaus. Both Atkeson and Kehoe (2007) and Jovanovic and Rousseau (2005) provide empirical evidence of this curve for other economic revolutions, including the IT revolution.

Together, (2) and (3) imply an aggregate condition:

$$S_t = \eta_s(N_{t+1} - \phi N_t)\mathbb{E}_t[M_{t+1}V_{t+1}]. \quad (4)$$

The left side denotes aggregate research expenditure and the right side summarizes the aggregate benefit of conducting research today: the increment of novel IT goods,  $(N_{t+1} - \phi N_t)$ , multiplied by each good's discounted expected value,  $\mathbb{E}_t[M_{t+1}V_{t+1}]$ , multiplied by the share of research revenue expensed during development,  $\eta_s$ .

Equations (3) and (4) are the key equations that link today's behavior of the financial market to tomorrow's dynamics in the real economy. To see this, plug (4) into (3) (and temporarily hold  $\eta_k = 0$  for clarity):<sup>13</sup>

$$\frac{N_{t+1}}{N_t} = \phi + (\bar{\theta}\eta_s^{\eta_s}\mathbb{E}_t[M_{t+1}V_{t+1}]^{\eta_s})^{\frac{1}{1-\eta_s}}, \quad (5)$$

This equation shows how IT firms have a profit-driven motive to innovate: the greater an IT good's value, which is closely tied to its demand, the greater the IT sector's growth rate. Thus, the model intimately links innovation and growth to entry and varieties of goods, an result consistent with empirical evidence presented by Jovanovic and MacDonald (1994).

## 2.2 Industrial sector

### Production function

The industrial sector comprises competitive firms that are identical. Because all firms are identical, the economy admits a representative firm. The representative firm produces a final good  $Y_t$  by combining capital  $K_t$ , a composite IT good  $G_t$ , and labor  $L_t$ , which is subject to a productivity shock  $A_t$ :

$$Y_t = (K_t^\alpha (A_t L_t)^{1-\alpha})^{1-m} G_t^m, \quad (6)$$

where  $m$  denotes the share of IT goods in factor income, and  $\alpha$  the capital share of non-IT good factor income.<sup>14</sup> I normalize the price of the final good to one. The production function specifies capital, IT goods, and labor as having positive cross-partial derivatives. Consequently, by renting more IT goods the marginal product of the two traditional inputs of production, capital and labor, increase.<sup>15</sup>

<sup>13</sup>This observation was made previously by Kung and Schmid (2012) and is emphasized again here.

<sup>14</sup>The definition of output here is that of gross output, which includes the output of intermediate goods. Jones (2011) states that gross output is twice as large as net output.

<sup>15</sup>Plant-level evidence on valve manufacturers by Bartel, Ichnowski and Shaw (2007) corroborates that the adoption of IT does more than simply replace factors: it enhances the productivity of them. Black and

## Composite IT good

At every date  $t$ , there is a varied continuum of measure  $N_t$  of IT goods. These information technology goods are bundled together into a composite good defined by a constant elasticity of substitution aggregator

$$G_t = \left[ \int_0^{N_t} X_t(g)^{\frac{1}{\mu}} dg \right]^{\mu}.$$

The parameter  $\mu$  measures the degree of variety that each IT good possesses. As  $\mu$  goes to one, all IT goods are perfect substitutes, and, furthermore, the incentive of the IT sector to conduct research goes to nil; consequently, growth is not sustained. Thus, I maintain the restriction that  $\mu > 1$ . A result of this restriction is that the industrial firm is more productive if, for example, it uses an equal amount of two IT goods versus if it uses twice as much of one IT good. Thus, when new IT goods are created, it is in the final-good producer's interest to diversify existing demand and include the new spectrum of goods, and to reduce the quantity demanded of each specific IT good. The variable  $G_t$  can be thought of as measuring the technological complexity of the final-good producers.

## Capital accumulation

I subject the accumulation of capital to Penrose-Uzawa adjustment costs, along the lines of Jermann (1998), with current capital depreciating at rate  $\delta$

$$K_{t+1} = (1 - \delta)K_t + \Lambda \left( \frac{I_t}{K_t} \right) K_t, \text{ where } \Lambda \left( \frac{I_t}{K_t} \right) = c_0 + \frac{c_1}{1 - \frac{1}{\zeta}} \left( \frac{I_t}{K_t} \right)^{1 - \frac{1}{\zeta}}. \quad (7)$$

The free parameters ( $c_0$  and  $c_1$ ) of the adjustment cost function are chosen to eliminate adjustment costs in the deterministic steady state (following Kaltenbrunner and Lochstoer (2010)).<sup>16</sup> The parameter  $\zeta \in (0, \infty)$  sets the elasticity of the investment rate with respect to marginal  $q$ , the expected marginal value of an additional unit of capital. If  $\zeta$  is low, marginal capital adjustment costs are high; as  $\zeta \rightarrow \infty$ , marginal capital adjustment costs go to zero.

## Stationary productivity

In addition, the exogenous source of total factor productivity (TFP) of the firm  $A_t$  follows

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Lynch (2001) additionally discover that greater computer usage by nonmanagerial employees raises plant productivity.

<sup>16</sup>Explicitly,  $c_0 = \frac{1}{1-\zeta}(g_N^* + \delta)$  and  $c_1 = (g_N^* + \delta)^{\frac{1}{\zeta}}$ , where the steady-state growth rate of IT goods is  $g_N^*$ . Note that  $\Lambda' \left( \frac{I_t}{K_t} \right) > 0$  and  $\Lambda'' \left( \frac{I_t}{K_t} \right) < 0$  for  $\zeta > 0$  and  $\frac{I_t}{K_t} > 0$ . Therefore the steady-state investment rate  $\frac{I}{K}^* = \Lambda \left( \frac{I}{K}^* \right) = g_N + \delta$ . Investment is always positive because  $\Lambda' \left( \frac{I_t}{K_t} \right)$  goes to infinity as  $\left( \frac{I_t}{K_t} \right)$  goes to zero.

a stationary Markov process<sup>17</sup>

$$\log(A_{t+1}) = \rho \log(A_t) + \epsilon_{t+1},$$

where  $\epsilon_{t+1}$  is an independently and identically distributed normal random variable with mean zero and constant variance  $\sigma_\epsilon^2$ . I set the autoregressive coefficient,  $\rho$ , near one, making exogenous productivity persistent.

### Maximization

Given an initial capital level of  $K_0$ , the firm chooses stochastic sequences of investment, labor, and IT goods  $\{I_t, L_t, \{X_t(g)\}_{g \in [0, N_t]}\}_{t \geq 0}$  to maximize the expected present value of dividends:

$$\mathbb{E}_t \left[ \sum_{s=0}^{\infty} M_{t|t+s} D_{t+s} \right], \text{ where } D_t = Y_t - I_t - W_t L_t - \int_0^{N_t} P_t(g) X_t(g) dg,$$

where  $M_{t|t+s} = M_{t+1} \cdot M_{t+2} \cdots M_{t+s}$  is the product of future stochastic discount factors from time  $t+1$  to  $t+s$ . The firm's optimality conditions are in Appendix A.

### Output and balanced growth

Using equilibrium conditions, I can rewrite (6) as

$$Y_t = \left( \frac{m}{\mu} \right)^{\frac{m}{1-m}} K_t^\alpha (A_t L_t)^{1-\alpha} N_t^{(\mu-1)\frac{m}{1-m}}. \quad (8)$$

To ensure balanced growth, the output equation must display constant returns to scale in reproducible factors (see Rebelo (1991))—capital and the measure of IT goods. Thus, a required parameter restriction for balanced growth is

$$\alpha + (\mu - 1) \frac{m}{1-m} = 1. \quad (9)$$

This restriction is interesting. Under the assumption that the long-run value of the IT-capital ratio has not yet been reached, it would be difficult to estimate what  $m$  is. The assumption of balanced growth, however, allows me to circumvent this issue by having  $m$  be pinned down by the estimates of  $\alpha$  and  $\mu$ , which are plausibly easier to measure today.

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<sup>17</sup>The Hicks-Neutral measurement of TFP would actually be  $A_t^{(1-\alpha)(1-m)}$ .

## 2.3 Resource constraint and households

### Resource constraint

The final good is used for consumption, and for investment in capital, IT, and research:

$$Y_t = C_t + I_t + N_t X_t + S_t. \quad (10)$$

Thus, total investment in this economy is the sum of capital investment,  $I_t$ , the total investment of the IT sector,  $N_t X_t$ , including its aggregate expenditure on research,  $S_t$ .

### Households

The economy is populated by a competitive representative household that derives utility from the consumption flow of the single consumption good  $C_t$ . It supplies labor perfectly inelastically, so  $L_t = 1$  for all  $t$ . The representative household maximizes the discounted value of future utility flows with Epstein and Zin (1989) and Weil (1989) recursive preferences:

$$U_t = \left\{ (1 - \beta) C_t^{1-1/\psi} + \beta (\mathbb{E}_t[U_{t+1}^{1-\gamma}])^{\frac{1-1/\psi}{1-\gamma}} \right\}^{\frac{1}{1-1/\psi}},$$

where  $\gamma$  is the coefficient of relative risk aversion,  $\psi$  is the elasticity of intertemporal substitution. I assume  $\psi > \frac{1}{\gamma}$ , so that the agent prefers the early resolution of uncertainty and dislikes shocks to long-run expected growth rates. This setup implies that the stochastic discount factor in the economy is given by

$$M_{t+1} = \beta \left( \frac{C_{t+1}}{C_t} \right)^{-\frac{1}{\psi}} \left( \frac{\mathbb{E}_t[U_{t+1}^{1-\gamma}]}{U_{t+1}^{1-\gamma}} \right)^{\frac{\gamma-1/\psi}{1-\gamma}}, \quad (11)$$

where the first term is the subjective discount factor, the second term reflects tomorrow's consumption growth, and the third term captures preferences concerning uncertainty about long-run growth prospects. The agent, therefore, requires compensation for these two sources of risk exposure. Indeed, sufficient exposure to persistent, long-run growth prospects creates a mechanism to generate large risk premia, as in Bansal and Yaron (2004) and Kung and Schmid (2012).

The household maximizes utility by choosing consumption, earning wage income, and participating in financial markets, taking prices as given. The household participates in financial markets by taking positions in the bond market  $B_t$  and in the stock market  $\mathcal{S}_t$ ,

which pays an aggregate stochastic dividend  $\mathcal{D}_t$ . The budget constraint of the household is

$$C_t + \mathcal{S}_{t+1}Q_t + B_{t+1} = W_tL_t + (Q_t + \mathcal{D}_t)\mathcal{S}_t + (1 + r_{f,t})B_t,$$

where  $\mathcal{S}_tQ_t$  is the aggregate market capitalization and  $(1 + r_{f,t})$  is the gross real rate of interest. The variables  $\mathcal{D}_t$  and  $Q_t$  are defined in (12) and (13).

## 2.4 The valuation-productivity link

### Stock-market valuation

The value of the stock market  $\mathcal{S}_tQ_t$  includes both the IT sector and industrial sector. I normalize the aggregate supply of stock  $\mathcal{S}_t$  to one. The aggregate dividend is the sum of the dividends paid by the industrial firm plus the total profits of the IT sector in excess of its expenditure on research:

$$\mathcal{D}_t \doteq \underbrace{D_t}_{\text{Industrial dividend}} + \underbrace{D_t^{IT}}_{\text{IT dividend}}, \quad (12)$$

where  $D_t^{IT} \doteq \Pi_t N_t - S_t$ . This leads to the following observations, whose proofs are in Appendix A, and which are central to the paper.

**Proposition** (Stock market valuation). *The aggregate value of the stock market in this economy is*

$$Q_t \doteq \underbrace{q_t K_{t+1}}_{\text{Industrial sector}} + \underbrace{N_t(V_t - \Pi_t)}_{\text{Assets-in-place}} + \underbrace{O_t}_{\text{Growth options}}, \quad (13)$$

*IT sector*

where  $O_t$  is defined as the value of IT sector's growth options:

$$O_t \doteq \mathbb{E}_t \left[ \sum_{s=1}^{\infty} M_{t|t+s} R_{t+s} \right] (1 - \eta_s).$$

**Corollary.** *If the returns to scale of doing research become constant ( $\eta_s = 1$ ), growth options embedded in the value of the IT sector become nonexistent and the future IT capital stock is not priced into today's market value.*

The value of the stock market, therefore, incorporates three elements: the replacement cost of installed capital, evaluated at the ex-dividend value of capital  $q_t K_{t+1}$ , and the value of IT firms, comprised of part assets-in-place and part growth options. Important is the

addition of the state variable  $N_{t+s}R_{t+s}$  to the third term. The value of the stock market contains information about the future level of  $N_{t+s}X_{t+s}$ , the future demand of IT, (which is proportional to  $N_{t+s}V_{t+s}$ ) and correspondingly the future stock of IT capital. Indeed, if the variety of IT goods is expected to expand, then a dear current market valuation can be justified, even if the current IT-capital ratio is low. When research is conducted subject to constant returns to scale, rents are not earned during research, eradicating the value of growth options in the IT sector, and the value of the IT sector would be simply be the value of assets-in-place,  $N_t(V_t - \Pi_t)$ .

### Price-dividend ratio

From (13), I define the IT sector's price-dividend ratio:

$$PD_t^{IT} \doteq \frac{N_t(V_t - \Pi_t) + O_t}{N_t\Pi_t - S_t} = \frac{\mathbb{E}_t \left[ \sum_{s=1}^{\infty} M_{t|t+s} D_{t+s}^{IT} \right]}{D_t^{IT}} \quad (14)$$

$$= \mathbb{E}_t \left[ \sum_{s=1}^{\infty} M_{t|t+s} \left( \frac{D_{t+s}^{IT}/N_{t+s}}{D_t^{IT}/N_t} \times \frac{N_{t+s}}{N_t} \right) \right]. \quad (15)$$

The last equation shows the information contained in the price-dividend ratio about economy-wide future growth. As the measure of IT goods is expected to grow, and thus contribute to the productivity of the industrial sector, the price-dividend ratio of the IT sector encodes this information and consequently will be high.

### Productivity

Given the restriction in (9), we can rewrite (8) as

$$Y_t = \left( \frac{m}{\mu} \right)^{\frac{m}{1-m}} K_t^\alpha (A_t N_t L_t)^{1-\alpha} \doteq K_t^\alpha (Z_t L_t)^{1-\alpha}. \quad (16)$$

Thus, our usual measurement of productivity is the product of two components: the exogenous, stationary component, and the endogenous, increasing mass of IT goods; call this product  $Z_t \doteq \left( \frac{m}{\mu} \right)^{\frac{m}{1-m}} A_t N_t$ . The adoption of IT goods showing up as immediate increases in measured productivity is consistent with the treatment of intermediate goods by Oberfield (2013), who writes a model where an entrepreneur's input choice of an intermediate good comes with an associated productivity-specific match.

Focusing on this product, a straightforward derivation for an arbitrary horizon  $h$  gives

$$\mathbb{E}_t \left[ \log \left( \frac{Z_{t+h}}{Z_t} \right) \right] = (\rho^h - 1) \log(A_t) + \mathbb{E}_t \left[ \log \left( \frac{N_{t+h}}{N_t} \right) \right]. \quad (17)$$

Because  $A_t$  is persistent, the first term on the right-hand-side of (17) is near zero (and slightly

negative). What does this last equation say? It says that the conditional expectation of the IT sector’s growth rate is the key for forecasting future productivity.

### 3 Empirical analysis

#### Predictive regression

The tight relationship between the decomposition of productivity in (17) and the IT sector’s price-dividend ratio in (15) is a strong prediction of the model. Does it hold in the data? I test this prediction with the following regression:

$$TFP_{t \rightarrow t+h} = a + b \times PD_t^{IT} + e_{t \rightarrow t+h},$$

where  $TFP_{t \rightarrow t+h} = TFP_{t+1} + \dots + TFP_{t+h}$  is the cumulative growth of TFP over  $h$  periods (the TFP variable is measured as the first difference of logarithms and is in percent), and the independent variable  $PD_t^{IT}$  is the annualized price-dividend ratio of the IT sector, which has been adjusted for repurchases (see Appendix B). Standard errors need to reflect the error term’s overlapping structure, which could potentially be serially correlated; for this reason, I use Hodrick (1992) standard errors, which should perform better than Newey and West’s (1987) adjustment because the former sums variances and avoids the latter’s summing of autocovariances, which are poorly estimated in small samples.

I report the results in Table 1 in two panels. Panel A documents economic significance. Consistent with a research expenditure affecting the economy with a lag, the effects of the price-dividend ratio are stronger at longer horizons. A greater valuation of IT goods leads to more research expenditure and, at a later date, the creation of new goods. The adoption of these new goods by the industrial sector coincides with gains in measured productivity growth. A unit change in the price-dividend ratio (from 50 to 51, for example) forecasts a 0.05 percentage point increase in TFP growth over the next four years. Real economic significance is ascertained, however, from the last column, which reports the expected change in TFP for a one standard-deviation change in the IT sector’s price-dividend ratio. Focusing on the four-year result, a one standard-deviation move in the price-dividend ratio increases TFP growth over the next four years by two percent, or nearly a half percent per year. To put this in perspective, real GDP growth per person is around two percent on average. Even more noteworthy are the adjusted R-squareds of the four- and five-year horizons: the price-dividend ratio explains effectively *half* of the variation in TFP growth over the period 1971–2012. I plot the time series for the price-dividend ratio and future cumulative TFP growth in Figure 1.

## Robustness

Panel B checks robustness by calculating the standard errors via the Newey and West (1987) adjustment and a Monte Carlo method. Due to the persistence of the predictor variable, estimates of the significance of the slope coefficient can be biased (see Stambaugh (1999)). To address this, I compute bias-adjusted small sample (Hodrick (1992))  $t$ -statistics and adjusted  $R$ -squareds, generated by bootstrapping 10,000 samples of the long-horizon regression under the null of no predictability.<sup>18</sup>

I further analyze this time-series prediction in Table 2. Horse races are run between the IT sector's and the industrial sector's price-dividend ratios. The IT sector's price-dividend ratio drives out the industrial sector's when comparing the two measures over all horizons. When adding the industrial sector's price-dividend ratio to the specification, the regression's adjusted  $R$ -squared does not increase by much. These results are consistent with the valuation and subsequent innovation in the IT sector driving the lion's share of future productivity growth in the industrial sector over this time period.

One would expect the estimated coefficients of this regression to change over time, with perhaps a greater economic effect being attributed to the early days of the transition. Table 3 lists the one-, three-, and five-year statistics from regressions estimated over various subperiods: an early period (1971Q1–1986Q4), an intermediate period (1986Q4–2002Q3), and a later period (2002Q3–2012Q4). The first two periods are chosen to have 63 quarters, starting from the sample start date; the second period is chosen to capture the dynamics of the dot-com boom; and the last period estimates the regression on the period following the boom.

Economically, the effects are larger the earlier the subperiod and almost monotonically wane as the transition unfolds, as measured by the standard deviation of the fitted value. Initially, the marginal product of an additional IT good is high, so a small increase in the IT-capital ratio shows up as a large gain in productivity. But in later periods, this marginal product falls over time, and with it the economically large gains in measured productivity. The changing slope of adjusted  $R$ -squareds, which begins steep but flattens and falls in later subperiods, corroborates this view.

Altogether, these regressions capture a central fact: the price-dividend ratio of the IT sector contains significant information about the future productivity of the economy.

One concern with the analysis is that the variation of future productivity growth is being explained only by variation in the valuation of the *public* IT sector, and thus could be biased.

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<sup>18</sup>This bootstrapping procedure follows Kilian (1999) and Goyal and Welch (2008). It preserves the autocorrelation of the predictor variable and the contemporaneous correlation of the predictive regression's and the predictor variable's shocks.

The price-dividend ratio employed, however, is constructed from value-weighted returns, as is described in Appendix B. In this case, the size of the bias would depend on magnitudes of two factors: the market value of the private firms and their price-dividend ratios. Accurately measuring the value of the private IT sector is difficult, simply because good data on this, to my knowledge, does not exist. Instead, I proxy the value of mature private firms—those likely to be genuine challengers or displacers of incumbents—as the total value of IPOs in a given year. Figure C plots the price-dividend ratio of the public IT sector versus a “true” estimate of the entire IT sector’s ratio over the period 1974 until 2012. The “true” estimate is a market-value weighted-average of price-dividend ratios. While not proof that my employed ratio is becoming unbiased, it is at least comforting that the divergence between the two ratios converges over time.

I now quantitatively analyze the model, from which I infer the duration and size of future productivity gains from the IT sector’s valuation.

## 4 Model analysis

I present the model analysis in two parts. I first calibrate some of the model’s common parameters to estimates in the literature. I then estimate the remaining parameters governing the structure of the IT sector in the second part, thus completing the specification of the model’s dynamics. In this second part, the model is simulated assuming it’s on a transition path, which starts the economy at an initial value that is different the long-run steady state of the model. Studying this transition path allows me to form predictions about the remaining length of the IT revolution and the accompanying growth in productivity.

The model is ran at a quarterly frequency. The equilibrium is computed numerically using a high-order perturbation method (Schmitt-Grohe and Uribe (2004)) that takes into account the high volatility of stock market prices. Note that the calibration here is unorthodox for two reasons: first, we do not observe the entire time series from which to estimate the parameters, because by assumption we are currently on the transition path and thus do not observe the data’s ergodic distribution; second, the exercise here is disciplined not by the moments of variables, but by each of their entire time series.

### 4.1 Calibration

Both the industrial sector’s and the household sector’s parameters have been calibrated in previous work. I discuss my choices here.

#### Industrial sector

The parameters here are  $\alpha$ ,  $\delta$ ,  $\zeta$ ,  $\rho$ , and  $\sigma_\epsilon$ . The ranges of these parameters have largely been agreed upon by the literature. A usual value for  $\alpha$  is in the neighborhood of a third, and I use a value of 0.3. I set the quarterly rate of depreciation  $\delta$  to 0.02, or around 8 percent at an annual rate. The adjustment cost parameter  $\zeta$  is set to 1.01, which falls in line with estimation evidence (see, for instance, Jermann (1998), Kaltenbrunner and Lochstoer (2010), and Croce (2012)). I choose the persistence parameter  $\rho$  to be an annualized value of 0.978 to match the first-order autocorrelation of consumption growth in the steady state. Finally, I pick the volatility of the exogenous TFP process  $\sigma_\epsilon$  to be 0.0175 to generate plausible macroeconomic volatilities.

### Households

Households are characterized by recursive preferences, which are governed by three parameters  $\gamma$ ,  $\psi$  and  $\beta$ . Substantial empirical work has been done on these parameters (see Bansal, Kiku and Yaron (2012)) and this is followed here by setting  $\gamma = 10$ ,  $\psi = 0.9$ , and lastly  $\beta = 0.9915$  to produce reasonable levels for both sectors' price-dividend ratios. The elasticity of substitution is usually assumed to be greater than one in much of the long-run risks literature (see, for example, Bansal and Yaron (2004) and Croce (2012)) to have the substitution effect dominate the wealth effect, leading positive innovations in expected growth to increase the price-dividend ratio. But it should be noted that *on the transition path* there is positive correlation between the sectors' price-dividend ratios and an eight-period moving average of measured TFP growth,  $\Delta \log(Z_t)$ , a proxy for expected growth. The model, moreover, requires an elasticity of substitution less than one to match the estimated time series relationship of factor loadings on the transition path, as will be described in the next section.

## 4.2 Estimation

### Information technology sector

The remaining six parameters governing the structure of the IT sector are calibrated and estimated here.

The IT share of factor income parameter  $m$  determines the importance of IT in the production. This is unknown by construction, because the steady state has not yet been observed. The choice is disciplined, however, by the balanced growth condition in (9) which specifies  $m$  given  $\mu$  and  $\alpha$ , two parameters that are plausibly easier to measure.

Five parameters  $\bar{\theta}$ ,  $\phi$ ,  $\eta_s$ ,  $\eta_k$ ,  $\mu$  are estimated using a simulated method of moments procedure:

$$b = (\bar{\theta}, \mu, \eta_s, \eta_k, \phi).$$

The method of moments estimator selects a vector of parameters that minimizes the distance between moments in the data and moments from simulated data produced from the model. I construct data from the Compustat Fundamentals file merged with equity data from CRSP. Details are in Appendix B.

Let  $\widetilde{M}$  denote the  $K \times 1$  vector of data moments. Given a parameter vector  $b$ , for each simulation,  $s = 1, \dots, S$ , I simulate a time series of length  $T$  and compute a vector of moments from the simulated data  $\widetilde{M}_s(b)$ . The method of moments estimator for the parameter vector  $b$  is defined as

$$\hat{b} = \underset{b}{\operatorname{argmin}} \left( \widetilde{M} - \frac{1}{S} \sum_{s=1}^S \widetilde{M}_s(b) \right)' W \left( \widetilde{M} - \frac{1}{S} \sum_{s=1}^S \widetilde{M}_s(b) \right), \quad (18)$$

where  $W$  is a positive, semi-definite weighting matrix. Following Duffie and Singleton (1993), I choose  $W = \Sigma_0^{-1}$ , where

$$\Sigma_0 = \sum_{j=-\infty}^{\infty} \mathbb{E}([m_t - \mathbb{E}[m_t]][m_{t-j} - \mathbb{E}[m_t]]'), \quad (19)$$

with  $\Sigma_0$  approximated using the estimator in Newey and West (1987) with three lags at the annual frequency and  $m_t$  denoting the date  $t$  observation in the data for each moment in the vector of moments  $\widetilde{M}$ . Duffie and Singleton (1993) show that under appropriate conditions

$$\sqrt{T}(\hat{b} - b_0) \xrightarrow{d} \mathcal{N}(0, \Omega_0), \quad (20)$$

where  $\Omega_0 = (1 + 1/S)(H_0' \Sigma_0^{-1} H_0)^{-1}$ ,  $b_0$  is the true vector of parameters, and

$$H_0 = \left. \frac{\partial \left[ \frac{1}{S} \sum_{s=1}^S \widetilde{M}_s(b) \right]}{\partial b} \right|_{b=\hat{b}}. \quad (21)$$

### Simulation procedure

For each parameter vector  $b$ , I solve the model and then simulate the economy 2,000 times ( $S = 2,000$ ) for 500 quarters ( $T = 500$ ) in the following two-step method:

1. Fix an initial IT-capital ratio  $\frac{N_0 X_0}{K_0}$  near the 1974 data point
2. Simulate,  $S$  times, an entire shock sequence,  $\{A_t\}_{t=1,2,\dots,T}$  for a given set of parameters  $b$  and compute model quantities and prices

I calibrate the model to match the initial IT-capital ratio to as close to the 1974 data point as possible, but I also require the model to be consistent with asset market data as well.

In each of these simulations, I compute the model's moments using only the first 38 years (152 quarters) of simulated, time-aggregated data, consistent with the length of the time series used to form estimates in the data. The remaining 348 quarters are used to describe the full dynamics of the system and estimate the remaining length of the IT revolution and the accompanying growth in productivity.

### **Selection of moments**

The selection of moments used is important to ensure the five parameters are identified. Note that the nature of the exercise is slightly different from that employed on a stationary model, where means, variances, and autoregressive coefficients usually characterize the stationary distribution. Here, I calibrate to the entire transition paths of several variables, essentially generating a time series vector for each variable, leaving open the possibility of selecting a very large number ( $K \times T$ ) of moments.

Instead, I compute the averages of several variables that would be expected to be informative about the transition path of the IT sector and further require that the simulated time series vectors of these variables be broadly consistent with the time series of these variables in the data. More specifically, I choose moments derived from the model's salient variables; namely, its factor shares, price-dividend ratios, growth rates, and discount rates.

The variables I choose are the average continuously compounded growth rates of the IT-capital ratio and the price-dividend ratios of the IT and the industrial sectors. I supplement these average growth rates with the average net entry rate and sales growth rate of the IT sector, and an estimate of IT sector markups, and mean estimates of real returns for both sectors, thus focusing the model's estimation on a range of macroeconomic and financial market data and reducing the number of moments to simply  $K = 8$ .

### **Analysis of transition paths**

In addition to calculating the transition path's simulated moments, I analyze the model's entire time series, which starts in 1974 and runs quarterly for 500 periods, past the time when the IT-capital ratio hits its long-run share at time  $\tilde{T}$ , which will now be defined. My focus on the IT-capital ratio is consistent with Jorgenson et al.'s (2011) conclusion that the chief contributor to recent economic growth was IT's growing factor share.

Consider a *convergence time*,  $\tilde{T}$ , adapted to the filtration  $\mathcal{F}_t$  that is defined as the first moment when the economy's IT-capital ratio has crossed its unconditional expected value

from below:

$$\begin{aligned}\tilde{T} &\doteq \inf \left\{ t : \frac{N_t X_t}{K_t} \geq \lim_{t \rightarrow \infty} \mathbb{E} \left[ \frac{N_t X_t}{K_t} \right] \right\} \\ &= \inf \left\{ t : \frac{N_t X_t}{K_t} \geq \left( \frac{m}{\mu} \right)^{\frac{1}{1-m}} \left[ \left( \frac{K}{N} \right)^* \right]^{\alpha-1} \exp \left\{ \frac{1}{2} (1-\alpha)^2 \frac{\sigma_\epsilon^2}{1-\rho^2} \right\} \right\},\end{aligned}\quad (22)$$

where  $(K/N)^*$  is the deterministic steady-state capital-IT good ratio, which is calculated numerically.<sup>19</sup> When the IT-capital ratio nears its long-run value, the interpretation is that the industrial sector has effectively tapped the major productivity gains that can be exploited from adopting IT and adjusting work practices to best use it.

With this definition of the convergence time, I am then able to estimate expected productivity growth in the future that is attributable to IT adoption by using the model to compare the simulated distributions of productivity growth from the period 1974 until 2013 with the period from 2013 until time  $\tilde{T}$ . I refer to time  $s > \tilde{T}$  as the model's (stochastic) *steady state*.

### Tests of model fit

Additionally, following Hennessy and Whited (2005), the technique provides a test of the overidentifying restrictions of the model with

$$\frac{T}{(1+1/S)} \left( \tilde{M} - \frac{1}{S} \sum_{s=1}^S \tilde{M}_s(\hat{b}) \right)' \tilde{W} \left( \tilde{M} - \frac{1}{S} \sum_{s=1}^S \tilde{M}_s(\hat{b}) \right), \quad (23)$$

converging to a Chi-squared distribution with degrees of freedom equal to the number of moments minus the number of parameters to be estimated, where  $\tilde{W} = [T \times \Sigma_0]^{-1}$ .

The median estimate of the convergence time is subject to the uncertainty with the parameter estimates. In order to address this uncertainty, I use a variant of the delta method used to estimate a standard error of the median estimate of  $\tilde{T}$ . More specifically, I estimate

$$\text{var}(\text{Median}(\tilde{T})) = \left. \frac{\partial \text{Median}(\tilde{T})}{\partial b} \right|_{b=\hat{b}}' \times \Omega_0 \times \left. \frac{\partial \text{Median}(\tilde{T})}{\partial b} \right|_{b=\hat{b}} \quad (24)$$

and take the square root of this estimate. The partial derivatives of  $\tilde{T}$  with respect to the parameter vector are calculated similarly to those calculated in (21) by numerically calculat-

<sup>19</sup>For intuition, assuming a deterministic model with a risk-neutral household with constant discount rate  $r$  gives a steady-state IT-capital ratio  $\left( \frac{NX}{K} \right)^* = \frac{(r+\delta)m}{(1-m)\alpha\mu}$ .

ing the difference between the average simulation perturbed by the parameters around the point estimate  $\hat{b}$ :

$$\left. \frac{\partial \text{Median}(\tilde{T})}{\partial b} \right|_{b=\hat{b}} = \left. \frac{\partial \left[ \frac{1}{S} \sum_{s=1}^S \text{Median}(\tilde{T})_s(b) \right]}{\partial b} \right|_{b=\hat{b}}. \quad (25)$$

## Estimation Results

Table 4 summarizes the estimates and calibration of parameters. I compare these estimates with some that I estimate in the data using reduced-form techniques.

The rate of obsolescence of an IT good  $1 - \phi$  in the model should capture two features: a high rate of economic obsolescence and default, as weaker firms without competitive advantages would be expected to exit the marketplace. A BEA report by Li (2012) lists a 16.5 percent annual depreciation rate for computers and electronics in a two-step estimation procedure that includes an adjustment for obsolescence. This rate is higher than the 15 percent rate applied by the BEA to generic research and development goods. In addition, I estimate the unconditional probability of defaulting using two methods, which are described in Appendix C. Both methods produce results near 3 percent. Because  $\phi$  is interpreted as a measure, I assume economic obsolescence and defaulting are independent and add the two measures together to get  $1 - \phi^{\text{Annual}} = 16.5 + 3 = 19.5$  percent, or nearly  $\phi = 0.95$  at a quarterly frequency, which is near with my estimation result of  $\hat{\phi} = 0.945$ .

To estimate  $\eta_s$  in the data, I approximate (5) to get

$$\log \left( \frac{N_{t+1}}{N_t} \right) \approx \frac{\eta_s}{1 - \eta_s} \log (\mathbb{E}_t [M_{t+1} V_{t+1}]),$$

and then substitute this equation into (16) to yield

$$\log \left( \frac{Z_{t+1}}{Z_t} \right) = (\rho - 1) \log(A_t) + \frac{\eta_s}{1 - \eta_s} \log (\mathbb{E}_t [M_{t+1} V_{t+1}]) + \epsilon_{t+1}.$$

This resembles a linear regression equation. It can be taken directly to the data to estimate  $\eta_s$ . I provide estimates in Table 6. Because the (log) price-dividend ratio better explains TFP variation at a longer horizon, estimates of the four- and five-year horizon are considered. Estimates at these horizons range from 0.69 to 0.93. Griliches (1990) also provides some estimates, which range from 0.6 to 1.0, depending on the use of cross-sectional or panel data. My estimate of 0.834 is within both ranges.

Estimating the parameter that governs the cost of capital readjustment  $\eta_k$  is difficult, and is one reason a simulated moments estimator was applied. My point estimate is -0.242. Note

that this estimate is disciplined by having this single parameter match the S-shaped diffusion dynamic of the IT-capital ratio, the transitions of both sectors' price-dividend ratios, and the IT sector's net entry and sales growth rates.

The parameter  $(\mu - 1)$  governs the average markup charged on IT goods. It is tough to measure accurately, especially given the IT sector's heterogeneity of products.<sup>20</sup> One study by Goeree (2008) finds that the median markups on personal computers across the total industry range from 5 to 15 percent, depending on the degree of information possessed by consumers in her limited-information model of consumer behavior. Moreover, direct estimates (see Table 5) based on the IT sector's average EBITDA-to-Sales ratio, a measure of markups, are 9.5 and 14 percent, depending if cross-sectional medians or aggregate means are used. My estimate of 13.4 percent is within these ranges.

Finally, the scale parameter,  $\bar{\theta}$ , is estimated to be to 1.66. This pins down overall growth rate of the economy in the steady state.

Altogether, the estimates taken from the simulated moments procedure appear to match well with those estimated in reduced-form exercises, which is comforting. In addition, the Chi-squared test statistic of the overidentifying restrictions, calculated in (23), is 5.69 and with  $8 - 5 = 3$  degrees of freedom does not produce a rejection of the model at the 10% level.

### 4.3 Discussion of estimation results

Rather than compare estimates of moments, which are simple averages of growth rates or returns, I demand a tougher test of the model and ask that its simulated sample paths closely match those of the data's. I now compare the IT-capital ratio, both sectors' price-dividend ratios, and the IT sector's average sales and net entry growth rates. The first path is the variable of interest. The latter four ensure that the model's asset pricing variables are consistent with financial market data. I discuss discount rates in the next section.

#### IT-capital ratio

Figure 3 plots the IT-capital ratio of the data versus that generated by the model. The IT-capital ratio data are only available up until 2006. Appendix B discusses in detail its construction. Overall, the model's average simulation does an excellent job of matching the time path of the IT-capital ratio. An important disciplining device is the model's other transitions.

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<sup>20</sup>For example, software and hardware manufacturers abide by different standards. Hardware manufacturers of chipsets, motherboards, and processors abide by an open standard: many motherboards, for example, can take RAM, hard drives, and GPUs from several manufacturers. Software manufacturers, conversely, often times have a dominant player; and this is a symptom of software standards being proprietary. The markup across these two manufacturers could vary considerably.

### Price-dividend ratios

The price-dividend ratio of the IT sector is defined in (15). The price-dividend ratio of the industrial sector is  $q_t K_{t+1}/D_t$ . In Figure 4 I plot the system's transitions. The model is able to match the industrial sector's price-dividend ratio to the time series data. Within its standard error bounds, the model can capture the run-up in prices during the dot-com boom and even the drop during Great Recession of 2008. The IT sector's price-dividend ratio of the model is able to capture the trend of the data, which is an important part of the analysis. The model's drop in the IT sector's ratio is consistent with that observed as well. The model has difficulty in generating the magnitude of the dot-com boom. Although this is not surprising because the model is not calibrated to match an episode of a "bubble". It is reassuring, however, that the data reverted back within the model's standard error bounds after the boom.

### IT sector average sales growth rates

I plot the transition of the IT sector's average sales growth rate in Figure 5. The model matches the fast, initial increase displayed by the data and then its drawn out path to convergence. This fast increase is consistent with a competition driving down the sales generated per firm. In the model, initially few firms dominate the marketplace. Over time, as more firms enter the marketplace, the industrial firm reduces the quantity demanded of each IT firm's good. Consequently, sales and profit earned per firm falls.

### IT sector net entry rates

I depict in Figure 6 the transition of the IT sector's net entry rate. The model matches the sharp decline displayed initially by the data and then its drawn out path to convergence. The model is unable to get its mean to be negative to match the data after the dot-com boom. The model, however, is able to match the negative data values because the model's lower confidence bound is negative. Note that a concentrating of firms is consistent with a "shake-out" period of an industry, which usually occur later in an industry's lifecycle.

### Risk exposures

The stochastic discount factor specified in (11) implies two sources of risk: the first source relates to innovations in realized consumption growth; the second source, to innovations in expected consumption growth. While there is only one source of risk to the economy ( $\epsilon_{t+1}$ ), the IT sector's innovation endogenously generates a low frequency source of risk—variability of expected consumption growth rates.

Following the literature on equity premia and long-run risk, this first source is termed short-run risk; the latter, long-run risk. The measurement of short-run risk is standard and

is taken to be the quarterly growth rate of real consumption of nondurables and services per capita in the data, and in the model it is simply the growth rate of  $C_t$ .

Long-run risk is measured in the model by the return on wealth ( $r_{C,t}$ ), which is directly measurable in the model, but needs to be estimated as a latent variable in the data.<sup>21</sup> In the data, I use three methods to estimate the long-run risk factor, which are described in Appendix C.

Both the short-run risk and long-run risk factors are standardized (to mean zero and variance one) before running the following regression for each sector  $i$  over a rolling 50-quarter window:

$$r_{i,t} = a_i + \beta_{i,cg}\Delta c_t + \beta_{i,rc}r_{C,t} + \nu_{i,t}, \quad \nu_t \stackrel{iid}{\sim} \mathcal{N}(0, \sigma_\nu^2).$$

Figure 7 plots rolling estimates of betas for both short-run risk and long-run risk of the IT sector and compares the model's estimates versus the data's. The model is able to match the data's upward trend in short-run risk exposure and its downward trend in the long-run risk exposure. The model is able to generate the correct direction and sign of these trends because it specifies the intertemporal elasticity of substitution to be less than one (the calibration uses 0.9). Specifying the elasticity to be greater than one changes the sign of each beta coefficient in the model from positive to negative at each date, thus producing trends that don't match with the data.

Figure 8 plots the entire transition path of risk loadings for both sectors. There is little change in the estimates of the industrial sector. The information technology sector, however, experiences a dramatic shift in sensitivities across the transition path. Why does it change? The sector becomes more exposed to short-run risk as the transition elapses. Because the initial size of IT sector is small, it absorbs a small amount of the risk to consumption. As the transition proceeds, IT becomes a larger part of the economy, and therefore absorbs a greater amount of the risk in consumption.

The sector's sensitivity to long-run risks is interesting. It starts positive, and then becomes negative, suggesting it becomes a hedge. Initially, as the economy is growing rapidly because of investment in IT, any adverse shock to long-run growth is a risk to the IT sector, because research is conducted in anticipation of tomorrow's value. As the sector matures, however, it becomes a hedge. An adverse shock to the expected growth rate benefits the IT sector, because it increases the potential for IT to generate growth in the future. In consequence, the price-dividend ratio and the return of the sector increase upon a realization of

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<sup>21</sup>The return on wealth in the model is defined recursively by the equation  $W_t = C_t + \mathbb{E}_t[M_{t+1}W_{t+1}]$  or equivalently by  $r_{C,t+1} \doteq \frac{W_{t+1}}{W_t - C_t}$ .

an adverse shock to long-run growth. Information technology, in the steady state, acts as a hedge against shocks to long-run growth.

Notice that in the model these factor loadings change as do the risk premia for both sectors over the transition. This time-variation in risk premia occurs without specifying stochastic volatility; in contrast, the traditional long-run risks framework requires stochastic volatility to generate time-varying risk premia (see Bansal and Yaron (2004)). Here, because the size of the IT sector as well as its ability to generate growth in the economy change over time, the model generates time-varying risk premia with homoskedastic shocks.

More generally, this finding has implications for empirical studies of asset pricing which use a particular sample to estimate parameters governing the dynamics of asset returns or the joint dynamics of consumption and asset returns. In particular, because the estimated loadings are changing over time, it is probable that the parameter estimates obtained in previous studies might not be representative of the secular pattern of the economy being investigated.

## Moments

I report in Table 7 the consumption growth statistics of the model in the steady state. The model matches the mean, standard deviation, and first-order autocorrelation of the data in the sample period 1974 until 2012. Having the model generate consistent growth and variability of consumption in the long-run is an imposition of the balanced growth condition in (9). This fit ensures the long-run behavior of the model is not counterfactual. It is important to get these statistics right because they determine the properties of the representative household's stochastic discount factor, and thus the correct discounting for the sectors' price-dividend ratios. The model generates a moderate degree of consumption smoothing, which is measured by the relative standard deviation of consumption to output. Total investment volatility is slightly smaller than in the data, but the model nevertheless generates a substantial amount.

The model is able to generate a risk-free rate that has both a low volatility and a high persistence as shown in Table 8. It is higher than commonly estimated because it is calibrated to match the levels of the sectors' price-dividend ratios.

In the same table, the equity returns for industrial stocks, IT stocks, and the aggregate stock market are reasonable once leverage is accounted for. A standard estimate of the required adjustment for leverage is two times that of an unlevered claim following Rauh and Sufi (2012). I estimate the IT sector's leverage to be 1.36 from Compustat data.

The model here is calibrated to match the transition paths and first moments of the salient asset market data over the last forty years. I argue that these low-frequency movements are the first-order concerns when choosing calibration targets. One shortcoming of

the model is its inability to generate substantial variation in risk premia, deriving partially from the model having only one source of exogenous variation that is calibrated to macroeconomic quantities. The standard deviation of returns in the model falls short of reaching the magnitudes estimated in the data. While volatility plays an important role in leading asset pricing research (for example, Bansal and Yaron (2004) and Ang, Hodrick, Xing and Zhang (2006)) and I acknowledge its importance in explaining macroeconomic variation at frequencies equal and greater than those of the business cycle, I find it less compelling that it drives variation in frequencies much lower than those at the business cycle and therefore regard the statistics as a second-order concern.

### Full dynamics

I provide intuition on four variables's average transition dynamics that are displayed in Figure 9. The top-left panel shows the transition path of the IT-capital ratio, the ratio of interest. It follows a S-shaped pattern because of how I specify the research externality. Initially, the rate of expansion of the IT sector is slow, because the capital reallocation friction, whose strength is indexed by the parameter  $\eta_k$ , drags heavily on research productivity. As time passes, the strength of this friction wanes; consequently, innovation begins feeding on itself, as the IT sector finds it easier to build new innovations on the top of existing ones. In the later stages of the transition, the marginal returns to both the IT sector innovating and the industrial sector employing IT subside, thereby reducing the rate of innovating and the expansion of IT. Because of the restriction on balanced growth, eventually IT capital, industrial capital, and the rest of the economy grow, on average, at the same rate.

The bottom-left panel displays the price-dividend ratios of the two sectors. Partly because the value of an IT good is initially very high, the price-dividend ratio of the IT sector is also high. The final-good firm's production function specifies positive cross-partial derivatives for capital and IT, so its value, as well, is higher than its steady state value. The price-dividend ratios converge to their steady-state levels nearly 10 years before the IT-capital ratio, highlighting asset market's forward-looking information that are contained in the IT sector's embedded growth options. The exercising of the growth options over the transition path is analogous to Gârleanu et al.'s (2012b) exposition on infrequent technological change.

The top-right panel plots quarterly productivity growth. Growth is much higher, on average, in the first half of the transition than in the latter half. This is because productivity growth is intimately tied to the IT sector's growth rate, and the valuation of an IT good. As the returns to innovating fall, the productivity gains of the economy fall as well.

The bottom-right panel features a marked drop in per firm profitability resulting from a decline in the quantity demanded for each IT good  $X_t$  that takes place as the IT sector grows. This is consistent with competition increasing for every firm as the transition runs its

course. This intensifying of competition lowers the returns to innovating, and puts a limit on the possible exceptional gains to growth from an expansion of the IT sector.

### Density of convergence times

Figure 10 plots the density of convergence times. The distribution is skewed right, and because of this I focus on the median estimate. The skewness arises because of a salient equilibrium effect of the model. A dear IT sector price-dividend ratio encourages research to develop new IT goods. These goods are subsequently rented, raising the industrial sector’s productivity. Importantly, greater industrial productivity increases its demand for IT goods, which feeds back into IT-good valuations. When the model is started at a low IT-capital ratio, IT is particularly valuable, so the dynamic is initially strong and puts the bulk of the distribution to the left of the mean.

The calibrated parameters imply that the steady-state IT-capital ratio,  $\lim_{t \rightarrow \infty} \mathbb{E} \left[ \frac{N_t X_t}{K_t} \right]$ , is 0.44, so for every 100 units of industrial capital, there 44 units of IT capital; in comparison, as of 2006—the last available data point—there are 18 and so the relative intensity of the use of IT capital is expected to more than double from 2006. The model’s median convergence time is 2035, and puts the revolution’s duration at 60 years.<sup>22</sup> The standard error around this median estimate is estimated from (24) and is 1.5 years. A two-standard error band puts the interval of the median convergence time between 2032 and 2038.

### Distributions of productivity

Finally, Figure 11 plots the distributions of historical TFP growth and model-implied future TFP growth. There are two things to notice. The first is that the historical distribution is much more symmetric than the future distribution. This is because both distributions are normalized per year, and the future distribution’s convergence time is random. Realizations of quick convergence times are coupled with high rates of TFP growth, generating a long, right tail.

The second is that the historical distribution’s mean is higher, by about a factor of about five-thirds (the historical distribution’s mean is 4.5% and the future distribution’s mean is 2.7%). This reflects the net entry rate of the IT sector. Initially, it is fast, but later it slows as the competition lessens the profitability of researching new IT goods. This leads to a prediction. Because of greater competition in the future than in the present, an IT good’s value will continue to fall, lowering the incentive to conduct research and to produce new IT goods. As a result, future TFP growth of the economy is expected to be lower than

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<sup>22</sup>The industrial revolution took 70 to 80 years, and the electrical revolution took around 40 years. Jovanovic and Rousseau (2005) show that IT has been diffusing across industries more slowly than electricity did. IT’s convergence time, therefore, should be expected to take longer.

before. To adjust the model’s calculation to bring it more in line with the data, I take the ratio of means to adjust the forecasted TFP growth rate per year. The historical average of utilization-adjusted TFP over the period 1971 until 2012 from the San Francisco Federal Reserve is 87 basis points. Therefore, expected TFP growth per year is  $0.87 \times 3/5 = 0.52$ , a reduction of 35 basis points.<sup>23</sup>

## 5 Conclusion

In this paper, I build an asset pricing model that endogenously links economy-wide growth to innovation in the IT sector, with an intensity is governed by the sector’s market valuation. Consistent with this link, I show empirically that the IT sector’s price-dividend ratio univariately explains nearly half of the variation in future productivity growth and that this empirical finding is robust and consistent with intuition. I then calibrate and estimate the model’s transition paths to match historical data on factor shares, price-dividend ratios, growth rates, and discount rates.

Future average annual productivity growth is predicted to fall to 52bps from the 87bps recorded over 1974–2012. This is due to both an intensifying of competition in the IT sector, which reduces the marginal benefit of it innovating, and decreasing returns in the broad economy’s employment of IT. My median estimate has a two-standard error band of 2032 to 2038, predicting that the IT sector’s transition six decades after its 1974 inception.

This new method I develop puts structure on financial market data to forecast future economic outcomes. I apply this methodology to study the IT sector’s transition towards its long-run share in the US economy, along with its implications for future growth. Future work could apply this methodology to revolutions of the past, such as the electricity revolution, to assess its predictive ability. It could also be applied in principle to study other phenomena, such as the discovery of a large, exhaustible energy resource.

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<sup>23</sup>This 35 basis point adjustment is similar to Robert J. Gordon’s “educational plateau adjustment” of 27 basis points he calculated in *The Economist*’s online debate, whose weblink is mentioned in the paper’s first footnote.

# A Proofs and derivations

## Constant markups

The price,  $P_t(g)$ , of IT good  $g$  is chosen to maximize the IT firm's profit. Take the quantity demanded,  $X_t(g) \doteq \arg \max_{X_t(g)} \Pi_t(g)$ , by the representative final-good firm for this particular good as given. Each monopolist solves the following static profit maximization problem each period:

$$\max_{P_t(g)} \Pi_t(g) \doteq P_t(g)X_t(g) - X_t(g)$$

Differentiating with respect to  $P_t(g)$  and plugging in (29) gives

$$\begin{aligned} P_t(g) &= 1 - \frac{X_t(g)}{\frac{\partial X_t(g)}{\partial P_t(g)}} \\ &= 1 - \frac{P_t(g)(1 - \mu)}{\mu}, \\ \Rightarrow P_t(g) &= \mu. \end{aligned}$$

Because the parameter  $\mu$  is independent of both time and a particular good, it holds for all  $g$  and  $t$ .

## First-order conditions

$$I_t : \quad q_t = \frac{1}{\Lambda' \left( \frac{I_t}{K_t} \right)} \quad (26)$$

$$K_{t+1} : \quad q_t = \mathbb{E}_t \left[ M_{t+1} \left\{ \alpha(1 - m) \frac{Y_{t+1}}{K_{t+1}} + q_{t+1} \left( (1 - \delta) - \Lambda' \left( \frac{I_{t+1}}{K_{t+1}} \right) \cdot \left( \frac{I_{t+1}}{K_{t+1}} \right) + \Lambda \left( \frac{I_{t+1}}{K_{t+1}} \right) \right) \right\} \right]. \quad (27)$$

$$L_t : \quad W_t = (1 - \alpha)(1 - m) \frac{Y_t}{L_t} \quad (28)$$

$$X_t(g) : \quad P_t(g) = (K_t^\alpha (A_t L_t)^{1-\alpha})^{1-m} \mu m \left[ \int_0^{N_t} X_t(g)^{\frac{1}{\mu}} dg \right]^{\mu m - 1} \frac{1}{\mu} X_t(g)^{\frac{1}{\mu} - 1}. \quad (29)$$

The first equation relates marginal  $q$  to the investment rate. The second equation is the usual Euler equation for capital policy. The third equation equates the marginal product of labor with the wage rate. The fourth is the derivative with respect to  $X_t(g)$ . Because the measure of IT goods,  $N_t$ , is a quantity not controlled by the activity of any single firm, it is treated as exogenous by the final-good firm.

## Stock market valuation

*Proof.* First, multiply (27) by  $K_{t+1}$  to give

$$\begin{aligned}
q_t K_{t+1} &= \mathbb{E}_t \left[ M_{t+1} \left\{ \alpha(1-m)Y_{t+1} + q_{t+1} \left( (1-\delta)K_{t+1} - \Lambda' \left( \frac{I_{t+1}}{K_{t+1}} \right) \cdot I_{t+1} + \Lambda \left( \frac{I_{t+1}}{K_{t+1}} \right) K_{t+1} \right) \right\} \right] \\
&= \mathbb{E}_t \left[ M_{t+1} \left\{ \alpha(1-m)Y_{t+1} + q_{t+1}K_{t+2} - q_{t+1}\Lambda' \left( \frac{I_{t+1}}{K_{t+1}} \right) \cdot I_{t+1} \right\} \right], \text{ by (7)} \\
&= \mathbb{E}_t [M_{t+1} \{ \alpha(1-m)Y_{t+1} - I_{t+1} + q_{t+1}K_{t+2} \}], \text{ by (26)}.
\end{aligned}$$

The first expression in the parentheses is output times the industrial firm's share of factor income attributed to capital, and the second is the firm's investment expenditure; the sum of the two gives the current dividend  $D_t$ . Iterating on the equation and imposing the transversality condition,  $\lim_{t \rightarrow \infty} \mathbb{E}_t M_{t|t+1} q_{t+1} K_{t+2} = 0$ , gives the result.

Next, I show two things. First, as the parameter governing the decreasing returns to research expenditure goes to one, the rents earned on research go to zero, and consequently the growth options embedded in the IT sector go to zero and therefore the future IT capital stock is not priced in today's market value. Second, I show that my definition of the IT sector's ex-dividend values is consistent with it being the expected discounted present value of dividends.

Exploiting the fact that  $S_t(f)$  equals  $S_t$  for all IT firms, a quick integration of firms across the IT sector shows that  $R_{t+1} = \theta_t S_t^{\eta_s} V_{t+1}$ . Expected discounted aggregate research profits then are

$$\begin{aligned}
\mathbb{E}_t [M_{t+1} R_{t+1}] - S_t &= (N_{t+1} - \phi N_t) \mathbb{E}_t [M_{t+1} V_{t+1}] - S_t \\
&= (N_{t+1} - \phi N_t) \mathbb{E}_t [M_{t+1} V_{t+1}] (1 - \eta_s),
\end{aligned}$$

where the first equality uses the law of motion for IT goods, equation (3), and the second equality uses the definition of aggregate research expenditure, equation (4).

With this observation we can define the growth options of the IT sector:

$$\begin{aligned}
O_t &\equiv \mathbb{E}_t \left[ \sum_{s=1}^{\infty} M_{t|t+s} \{ V_{t+s} (N_{t+s} - \phi N_{t+s-1}) - S_{t+s} \} \right] = \mathbb{E}_t \left[ \sum_{s=1}^{\infty} M_{t|t+s} \{ R_{t+s} - S_{t+s} \} \right] \\
&= \mathbb{E}_t \left[ \sum_{s=1}^{\infty} M_{t|t+s} R_{t+s} \right] (1 - \eta_s)
\end{aligned}$$

where I used the law of iterated expectations (for  $s > t$ ):  $E_s[S_s] = (N_{s+1} - \phi N_s) \mathbb{E}_s[M_{s+1} V_{s+1}] \eta_s$ . Thus as  $\eta_s \rightarrow 1$ , rents from research go to zero and the future IT capital stock,  $N_{t+s} X_{t+s}$ , which is proportional to  $N_{t+s} V_{t+s}$ , is not priced in today's market value. I'll now show the ex-dividend value of the IT sector is simply the expected discounted present value of dividends:

$$\begin{aligned}
N_t(V_t - \Pi_t) + O_t &= \phi \mathbb{E}_t [M_{t+1} V_{t+1}] N_t + \mathbb{E}_t [M_{t+1} V_{t+1} (N_{t+1} - \phi N_t) - M_{t+1} S_{t+1} + M_{t+1} O_{t+1}] \\
&= \mathbb{E}_t [M_{t+1} V_{t+1} N_{t+1} - M_{t+1} S_{t+1} + M_{t+1} O_{t+1}] \\
&= \mathbb{E}_t [M_{t+1} \{ \Pi_{t+1} N_{t+1} - S_{t+1} + (V_{t+1} - \Pi_{t+1}) N_{t+1} + O_{t+1} \}].
\end{aligned}$$

Iterating this equation forward and assuming  $\lim_{t \rightarrow \infty} E_t [M_{t|t+1} (V_{t+1} - \Pi_{t+1}) N_{t+1}] = 0$  and  $\lim_{t \rightarrow \infty} E_t [M_{t|t+1} O_{t+1}] = 0$  proves the claim.  $\square$

## B Data construction

### Macroeconomic and financial data

The macroeconomic data I use begins in 1974, a year thought by leading growth economists to be the inception of the IT revolution (Greenwood and Yorukoglu (1997), Greenwood and Jovanovic (1999), Hobijn and Jovanovic (2001)). It is also the year after CRSP added the NASDAQ index to its database. Moreover, the first Intel microprocessor suitable for desktop use, the “4004”, was commercialized 1971, spawning the PC industry. My financial market data begins earlier in 1971, allowing me to apply the Hodrick-Prescott filter before having this data share the same 1974 start date.

Data on US consumption of nondurables and services, gross domestic product, nonresidential, private, fixed investment, and population are from the National Income and Product Accounts of the Bureau of Economic Analysis. Data on the value-weighted market’s price-dividend ratio are from CRSP. Risk-free returns are from Ken French’s data library. Consumer price index inflation and the spread between Baa and Aaa corporate bonds are obtained from the St. Louis FRED. The TFP measure comes in two forms—adjusted and non-adjusted—from the San Francisco Fed. The adjusted measure adjusts for variation in capacity utilization and hours worked within a workweek.

### Construction of IT-capital ratio

Consistent with Jorgenson et al.’s (2011) work, I measure information technology as the sum of hardware, software, and communications capital. I treat it as a type of capital that is distinct from industrial capital. I refer to the former as “IT”, and to the latter as “capital”. Both types refer to stocks of a quantity of “machines” and are measured in units. Hence, the IT-capital ratio is analogous to a capital-labor ratio, both ratios being a relative intensity of factor use.

Dale Jorgenson provides data from 1948 until 2006 through Harvard’s DataVerse, a public database, for two of the four series of interest: the price and value of capital *services* of IT capital, and the price and value of the capital *stock* of tangible capital. The two remaining series required, however, are the capital *service* price and value series for tangible capital, which are not provided on DataVerse.

A capital service of an input measures the flow of services from a quality-adjusted index of the stock of the input. Jorgenson assumes a constant quality and thus the service flow from a stock for each asset within an input is a *constant*—so capital service flows match capital quantity stocks. Using a quality-adjusted service flow, especially for a quickly changing input such as IT, is the best estimate of an input’s periodic factor income, which has a close analog to quantities employed in theoretical macroeconomic models, like the one presented in this paper.

Jorgensen estimates the capital service series from the capital stock series in great detail. While a genuine updated series would be preferred, the task requires a tremendous amount of work. Estimates of depreciation rates, price indices, quantity indices, investment tax credits, capital consumption allowances, corporate and personal tax rates, property taxes, and debt versus equity financing values are required for estimates of after-tax real rates of return for *each* of the 65 investment classifications of the Bureau of Economic Analysis. See Appendix B in Jorgenson and Stiroh (2000) for details on this. In place of this, the following was performed:

- Both price and value series of both capital stock and capital service series for tangible capital were taken from Jorgenson and Stiroh (2000, Table B2, p. 74), which covers the years 1959-1998.
- Linear regressions were run of the ratio of services to stock on a constant for both the price and value

series. This estimate provided a measure of an average service flow that is derived from the stock. The fit in both regressions resulted in R-squareds of over 98 percent.

- The estimates for the value and price series were then multiplied by their respective tangible capital stock series supplied by DataVerse to get estimates of the longer time series capital services measure.

Finally, for both IT and capital, the value series was divided by the price series to compute a quantity series for both IT capital services and industrial capital services, which have close analogs to the quantities  $N_t X_t$  and  $K_t$  in the model. These two quantity series were divided to construct the data's counterpart to the ratio of interest, the IT-capital ratio.

### **IT sector definition**

For financial market data, I use the term “information technology” to describe the collection of technologies related to computer software, computer hardware, communications equipment, and those employed by technical consultants hired either to incept or to enhance an adopting company's use of information technology. This latter qualification arises because large producers of IT, like IBM, sell consulting services along with IT itself. Earnings from this service would show up in IBM's financial market data.

Data are from Chicago's Center for Research in Security Prices and Compustat. Data are restricted to stocks trading on the NYSE, AMEX, and NASDAQ exchanges, having share codes 10 and 11, and being US-headquartered firms. A firm is classified as being in the IT sector if it has one of the following North American Industrial Classification System (NAICS) four-digit codes:

- 3341 - Computer and peripheral equipment manufacturing
- 3342 - Communications equipment manufacturing
- 3344 - Semiconductor and other electronic component manufacturing
- 5112 - Software publishers
- 5172 - Wireless telecommunications carriers (except satellite)
- 5174 - Satellite telecommunications
- 5182 - Data processing, hosting, and related services
- 5191 - Other information services (includes Internet publishing and broadcasting and web search portals)
- 5415 - Computer systems design and related services
- 5416 - Management, scientific, and technical consulting services

A firm's Compustat NAICS code is preferred over a firm's CRSP code, when codes conflict, because Compustat NAICS data are more complete and CRSP switched NAICS data sources from Mergent to Interactive Data Corporation in December 2009, possibly changing some firms' classifications. I use primary NAICS codes that are assigned to each firm and that matches its primary activity—generally the activity that generates the most revenue for the establishment.

### **Price-dividend ratios**

Price-dividend ratios are from the CRSP annual value-weighted return series with and without dividends.

These series are defined as

$$R_{t+1} \doteq \frac{P_{t+1} + D_{t+1}}{P_t}, \quad RX_{t+1} \doteq \frac{P_{t+1}}{P_t}.$$

Price-dividend ratios are then constructed as the inverse of

$$\frac{D_{t+1}}{P_{t+1}} = \frac{R_{t+1}}{RX_{t+1}} - 1. \quad (30)$$

By using an annual horizon, the strong seasonal component of dividends is attenuated, even when using monthly or quarterly observations. This definition reinvests dividends to the end of the year, consistent with the methodology of Cochrane (2011).

Because the incidence of firms which repurchase shares has increased, an alternative measure of payouts to equity shareholders is used.<sup>24</sup> Following Bansal, Dittmar and Lundblad (2005), for every month, denote the number of shares at time  $t$  after adjusting for splits, stock dividends, et cetera (using the CRSP share adjustment factor) as  $n_t$ . An adjusted capital gain series is constructed for a given firm:

$$RX_{t+1}^* = \left[ \frac{P_{t+1}}{P_t} \right] \max \left\{ 0.95, \min \left\{ \frac{n_{t+1}}{n_t}, 1 \right\} \right\}.$$

The construction differs from that of Bansal et al.'s (2005) because of the additional maximum operator above, which trims the amount of a repurchase to a maximum of 5 percent of a stock's total shares outstanding. Without this additional operator, the price-dividend ratios are significantly affected by outliers, especially the IT sector's in the early 1970s when few firms are classified (only 134 firms by 1974). Bounds at 0.8 and 0.9 result in similar price-dividend ratio series. I select a value of 95 percent because the probability of observing a share repurchase greater than 5 percent in a month is 1 percent for both sectors, consistent with usual winsorization practices. As a case in point, FactSet, a data service, reports the largest share repurchaser, as a percentage of total shares outstanding, was Seagate Technology, a manufacturer of hard drives, which repurchased 35.2 percent of its shares outstanding in 2012, or about 3 percent per month.<sup>25</sup>

I also constructed another valuation measure similar to Grullon and Michaely's (2002), which is based on the actual repurchase dollar amounts of common shares in Compustat. For this measure, dividends were constructed as trailing twelve-month sums. The price-dividend ratio of this Compustat-based series was similar to the CRSP-based series construction above.

I created and considered price-earnings ratios as well. The time series dynamics are similar to those of the dividend series. They are not the preferred series, however, because IT firms spend relatively more money on research than do non-IT firms (see footnote 13). Research can be classified by management as either an expenditure before taxes and earnings or as investment in a capital asset. Thus, this discretion can be used to manipulate earnings. Furthermore, the model has firms pay out all excess cash flows as dividends and hence do not make a dividend distribution decision based on earnings, and so using the price-dividend ratio in the data is a closer match to the model's assumptions.

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<sup>24</sup>Fama and French (2001) document that the proportion of firms paying dividends falls after the introduction of the NASDAQ index in 1973; moreover, estimates from a logistic regression model suggest the propensity to pay dividends also declined. Grullon and Michaely (2002) provide evidence of a SEC regulatory change (Rule 10b-18) which occurred in 1982 granted a safe harbor for repurchasing firms against the previously considered manipulative practice. Repurchase activity, consequently, is much larger post-1983.

<sup>25</sup>Details are provided at "<http://www.factset.com/>" under the BuyBack Quarterly report, 2 April 2013.

# C Estimation of default and the return on wealth

## Estimation of default

Following Campbell, Hilscher and Szilagyi (2008) and Boualam, Gomes and Ward (2012), I proxy default with performance-related delisting events on CRSP.<sup>26</sup> I use two methods. First, I simply compute the frequency of delisting and divide it by the starting count of firms for each year for the IT sector. Second, I compute annual percentage change in the number of IT firms for each year, and take the minimum of this measure and a value of zero to only count observations that are negative:

$$\min \left[ \frac{n_{t+1} - n_t}{n_t}, 0 \right],$$

where  $n_t$  is the number of IT firms at year  $t$ , sampled at an annual frequency. I then temporally average both methods to estimate the unconditional probability of default. Both methods produce results near 3 percent.

## Estimation of long-run risk

I use three methods to estimate the return on the wealth portfolio (long-run risk) in the data:

1. Kalman filter
2. Predictive regression
3. Vector autoregression

In what follows, all variables have been demeaned, and all errors below are assumed to be *iid* standard normal random variables. Estimates are detailed in Table C. The Kalman filter method follows Croce (2012). The long-run risk component is estimated via the following system:

$$\begin{aligned}\Delta c_{t+1} &= x_t + \sigma \nu_{t+1} \\ x_{t+1} &= \rho x_t + \sigma \eta_{t+1}.\end{aligned}$$

The Kalman filter estimates the latent state  $x_t$  and treats it as the long-run risk component  $r_{C,t}$ . It is estimated by maximum likelihood.

The predictive regression approach follows Colacito and Croce (2011) where tomorrow's consumption growth is regressed on the value-weighted market price-dividend ratio, the risk-free rate, lagged consumption growth, the consumption-output ratio, and a measure of default risk (the Baa-Aaa spread):

$$\Delta c_{t+1} = \beta X_t + \sigma \nu_{t+1}, \text{ where } X_t = \{\Delta c_t, pd_t, r_{f,t}, cy_t, def_t\}.$$

The long-run risk component can be extracted by projecting tomorrow's consumption growth onto today's state variables  $X_t$ :  $r_{C,t} = \text{proj}[\Delta c_{t+1}|X_t] = \hat{\beta} X_t$ .

Finally, specifying a vector autoregression using the same state vector as above

$$X_{t+1} = AX_t + \Sigma \nu_{t+1}$$

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<sup>26</sup>Delisting codes used are 500, 550, 552, 560, 561, 574, 580, and 584. They are defined at <http://www.crsp.com/products/documentation/delisting-codes>.

can be used to extract the long-run risk component, the expected discounted value of consumption growth over the infinite horizon:

$$r_{C,t} = \mathbb{E}_t \left[ \sum_{s=0}^{\infty} \kappa^s \Delta c_{t+s} \right] = (1 - \kappa A)^{-1} X_t \mathbf{1}_{\Delta c_t},$$

where  $\mathbf{1}_{\Delta c_t}$  is an indicator that picks out the vector associated with consumption growth. The discount factor  $\kappa$  is related to the unconditional mean of the price-consumption ratio as in Campbell and Shiller (1988). I set it to 0.965, a value consistent with Lustig, Nieuwerburgh and Verdelhan's (2013) work. Results are not dependent on this setting.

### Table A: Estimates of return on wealth (long-run risk)

Panel A reports the maximum likelihood estimates of a Kalman filter to extract the return on wealth using only consumption data. Panel B reports the VAR coefficients of the matrix  $A$ . The results from the predictive regression follow from using the predicted values of the top row in the  $A$  matrix. Data are quarterly and cover the years 1971–2012. Data construction is described in Appendix B.

#### Panel A: Kalman filter estimates

Parameter	Estimate
$\rho$	0.78***
$\sigma$	0.0024***
$p < 0.01$ - ***	

#### Panel B: VAR estimates

	$\Delta c_t$	$PD_t^{\text{MKT}}$	$r_t^f$	$cy_t$	$def_t$
$\Delta c_{t+1}$	0.448***	0.000	-0.0003***	-0.049***	-0.001
$PD_{t+1}^{\text{MKT}}$	128.03***	0.974***	0.1239*	19.58***	-1.119***
$r_{t+1}^f$	6.978	-0.008	0.907***	-7.022*	-0.299*
$cy_{t+1}$	-0.184***	0.00005***	0.0003***	0.99***	0.000
$def_{t+1}$	-8.91**	0.000	0.019***	0.610	0.812***

OLS standard errors  $p < 0.01$  - \*\*\*,  $p < 0.05$  - \*\*,  $p < 0.1$  - \*

## References

- Abel, Andrew B. and Janice C. Eberly, "Investment, Valuation, and Growth Options," *The Quarterly Journal of Finance*, March 2012, 2 (1).
- Acemoglu, Daron, *Introduction to Modern Economic Growth*, Princeton University Press, 2009.
- Aghion, Phillipe and Peter Howitt, "A Model of Growth Through Creative Destruction," *Econometrica*, March 1992, 60 (2), 323–351.
- Ang, Andrew, Robert J. Hodrick, Yuhang Xing, and Xiaoyan Zhang, "The Cross-Section of Volatility and Expected Returns," *The Journal of Finance*, February 2006, 61 (1), 259–299.
- Atkeson, Andrew and Patrick J. Kehoe, "Modeling the Transition to a New Economy: Lessons from Two Technological Revolutions," *The American Economic Review*, March 2007, 97 (1), 64–88.
- Bakos, Yannis and Erik Brynjolfsson, "Bundling Information Goods: Pricing, Profits, and Efficiency," *Management Science*, December 1999, 45 (12), 1613–1630.
- Bansal, Ravi and Amir Yaron, "Risks for the Long Run: A Potential Resolution of Asset Pricing Puzzles," *The Journal of Finance*, August 2004, 59 (4), 1481–1509.
- , Dana Kiku, and Amir Yaron, "An Empirical Evaluation of the Long Run Risks Model for Asset Prices," *Critical Finance Review*, 2012, 1, 183–221.
- , Robert F. Dittmar, and Christian T. Lundblad, "Consumption, Dividends, and the Cross Section of Equity Returns," *The Journal of Finance*, August 2005, 60 (4), 1639–1672.
- Bartel, Ann, Casey Ichnowski, and Kathryn Shaw, "How Does Information Technology Affect Productivity? Plant-level Comparisons of Product Innovation, Process Improvement, and Worker Skills," *Quarterly Journal of Economics*, November 2007, 122 (4), 1721–1758.
- Beaudry, Paul and Franck Portier, "An Exploration Into Pigou's Theory of Cycles," *Journal of Monetary Economics*, September 2004, 51 (6), 1183–1216.
- and —, "Stock Prices, News, and Economic Fluctuations," *The American Economic Review*, September 2006, 96 (4), 1293–1307.
- Belo, Frederico, "Production-Based Measures of Risk for Asset Pricing," *Journal of Monetary Economics*, March 2010, 57 (2), 146–163.
- Berk, Jonathan B., Richard C. Green, and Vasant Naik, "Optimal Investment, Growth Options, and Security Returns," *The Journal of Finance*, October 1999, 54 (5), 1553–1607.
- Black, Sandra E. and Lisa M. Lynch, "How to Compete: The Impact of Workplace Practices and Information Technology on Productivity," *The Review of Economics and Statistics*, August 2001, 83 (3), 434–445.
- Boualam, Yasser, Joao F. Gomes, and Colin Ward, "Understanding the Behavior of Distressed Stocks," December 2012. Working paper.
- Brynjolfsson, Erik and Andrew McAfee, *Race Against The Machine: How the Digital Revolution is Accelerating Innovation, Driving Productivity, and Irreversibly Transforming Employment and the Economy*, Digital Frontier Press, 2011.

- Byrne, David M., Stephen D. Oliner, and Daniel E. Sichel**, “Is the Information Technology Revolution Over?,” Technical Report 25, Centre for the Study of Living Standards Spring 2013. International Productivity Monitor.
- Campbell, John Y. and Robert J. Shiller**, “The Dividend-Price Ratio and Expectations of Future Dividends and Discount Factors,” *Review of Financial Studies*, 1988, *1*, 195–228.
- , **Jens Hilscher, and Jan Szilagyi**, “In Search of Distress Risk,” *The Journal of Finance*, December 2008, *63* (6), 2899–2939.
- Carlson, Murray, Adlai Fisher, and Ron Giammarino**, “Corporate Investment and Asset Price Dynamics: Implications for the Cross-section of Returns,” *Journal of Finance*, December 2004, *59* (6), 2577–2603.
- Cochrane, John H.**, “A Cross-Sectional Test of an Investment-Based Asset Pricing Model,” *The Journal of Political Economy*, June 1996, *104* (3), 572–621.
- , “Stocks as Money: Convenience Yield and the Tech-Stock Bubble,” in William C. Hunter, George G. Kaufman, and Michael Pomerleano, eds., *Asset Price Bubbles: The Implications for Monetary, Regulatory, and International Policies*, Cambridge and London: MIT Press, 2003.
- , “The Dog that Did Not Bark,” *Review of Financial Studies*, 2006, *21*, 1533–1575.
- , “Presidential Address: Discount Rates,” *The Journal of Finance*, August 2011, *66* (4), 1047–1108.
- Colacito, Riccardo and Mariano M. Croce**, “Risks for the Long Run and the Real Exchange Rate,” *Journal of Political Economy*, February 2011, *119* (1), 153–181.
- Comin, Diego and Mark Gertler**, “Medium-Term Business Cycles,” *The American Economic Review*, June 2006, *96* (3), 523–551.
- Cowen, Tyler**, *The Great Stagnation: How America Ate All the Low-Hanging Fruit of Modern History, Got Sick, and Will (Eventually) Feel Better Again*, Dutton, 2011.
- Croce, Mariano Massimiliano**, “Long-run Productivity Risk: A New Hope for Production-Based Asset Pricing?,” May 2012. SSRN working paper 1106361.
- Duffie, Darrell and Kenneth J. Singleton**, “Simulated Moments Estimation of Markov Models of Asset Prices,” *Econometrica*, July 1993, *61* (4), 929–952.
- Epstein, Larry G. and Stanley E. Zin**, “Substitution, Risk Aversion, and the Temporal Behavior of Consumption and Asset Returns: A Theoretical Framework,” *The Journal of Finance*, July 1989, *57* (4), 937–969.
- Fama, Eugene F. and Kenneth R. French**, “Disappearing Dividends: Changing Firm Characteristics or Lower Propensity to Pay?,” *Journal of Financial Economics*, 2001, *60*, 3–43.
- Gala, Vito**, “Irreversible Investment and the Cross-Section of Stock Returns in General Equilibrium,” 2010. Working paper.
- Gârleanu, Nicolae, Leonid Kogan, and Stavros Panageas**, “Displacement Risk and Asset Returns,” *Journal of Financial Economics*, September 2012, *105* (3), 491–510.

- , **Stavros Panageas**, and **Jianfeng Yu**, “Technological Growth and Asset Pricing,” *The Journal of Finance*, August 2012, *67* (4), 1265–1292.
- Goeree, Michelle Sovinsky**, “Limited Information and Advertising in the US Personal Computer Industry,” *Econometrica*, September 2008, *76* (5), 1017–1074.
- Gomes, João F., Leonid Kogan, and Lu Zhang**, “Equilibrium Cross-Section of Returns,” *Journal of Political Economy*, August 2003, *111* (4), 693–732.
- , —, and **Motohiro Yogo**, “Durability of Output and Expected Stock Returns,” *Journal of Political Economy*, October 2009, *117* (5), 941–986.
- Goolsbee, Austan and Peter J. Klenow**, “Evidence on Learning and Network Externalities in the Diffusion of Home Computers,” *Journal of Law and Economics*, October 2002, *45*, 317–343.
- Gordon, Robert J.**, “Does the New Economy Measure up to the Great Inventions of the Past?,” *Journal of Economic Perspectives*, Fall 2000, *14* (4), 49–74.
- , “Is U.S. Economic Growth Over? Faltering Innovation Confronts the Six Headwinds,” August 2012. NBER Working paper No. 18315.
- , “Is U.S. Economic Growth Over? Faltering Innovation Confronts the Six Headwinds,” Technical Report 25, Centre for the Study of Living Standards Spring 2013. International Productivity Monitor.
- Gourio, François**, “Disaster Risk and Business Cycles,” *American Economic Review*, October 2012, *102* (6), 2734–66.
- Goyal, Amit and Ivo Welch**, “A Comprehensive Look at The Empirical Performance of Equity Premium Prediction,” *The Review of Financial Studies*, 2008, *21* (4), 1455–1508.
- Greenwood, Jeremy and Boyan Jovanovic**, “The Information-Technology Revolution and the Stock Market,” *The American Economic Review*, May 1999, *89* (2), 116–122.
- and **Mehmet Yorukoglu**, “1974,” *Carnegie-Rochester Conference Series on Public Policy*, June 1997, *46*, 49–95.
- , **Zvi Hercowitz**, and **Per Krusell**, “Long-Run Implications of Investment-Specific Technological Change,” *The American Economic Review*, June 1997, *87* (3), 342–362.
- Griliches, Zvi**, “Patent Statistics as Economic Indicators: A Survey,” *Journal of Economic Literature*, December 1990, *28* (4), 1661–1707.
- Grossman, Gene M. and Elhanan Helpman**, *Innovation and Growth in the Global Economy*, MIT Press, 1991.
- Grullon, Gustavo and Roni Michaely**, “Dividends, Share Repurchases, and the Substitution Hypothesis,” *The Journal of Finance*, August 2002, *57* (4), 1649–1684.
- Hennessy, Christopher A. and Toni M. Whited**, “Debt Dynamics,” *The Journal of Finance*, June 2005, *60* (3), 1129–1165.
- Hobijn, Bart and Boyan Jovanovic**, “The Information-Technology Revolution and the Stock Market: Evidence,” *The American Economic Review*, December 2001, *91* (5), 1203–1220.

- Hodrick, Robert J.**, “Dividend Yields and Expected Stock Returns: Alternative Procedures for Inference and Measurement,” *Review of Financial Studies*, 1992, 5 (3), 357–386.
- Jaruzelski, Barry, John Loehr, and Richard Holman**, “The 2012 Global Innovation 1000 Study: Making Ideas Work,” Technical Report, Booz and Company 2012.
- Jermann, Urban J.**, “Asset Pricing in Production Economies,” *Journal of Monetary Economics*, February 1998, 41 (2), 257–275.
- Jones, Charles I.**, “Intermediate Goods and Weak Links in the Theory of Economic Development,” *American Economic Journal: Macroeconomics*, April 2011, 3, 1–28.
- Jorgenson, Dale W. and Kevin J. Stiroh**, “Raising the Speed Limit: US Economic Growth in the Information Age,” *Brookings Papers on Economic Activity*, February 2000, 31 (1), 126–236.
- , **Mun S. Ho, and Jon D. Samuels**, “Information Technology and US Productivity Growth: Evidence from a Prototype Industry Production Account,” *Journal of Productivity Analysis*, 2011, 36, 159–175.
- Jovanovic, Boyan and Glenn M. MacDonald**, “The Life Cycle of a Competitive Industry,” *Journal of Political Economy*, April 1994, 102 (2), 322–347.
- and **Peter L. Rousseau**, “General Purpose Technologies,” in Philippe Aghion and Steven N. Durlauf, eds., *Handbook of Economic Growth*, Vol. 1, Elsevier B.V., 2005, chapter 18, pp. 1182–1221.
- Kaltenbrunner, Georg and Lars A. Lochstoer**, “Long-Run Risk through Consumption Smoothing,” *The Review of Financial Studies*, 2010, 23 (8), 3190–3224.
- Kilian, Lutz**, “Exchange Rates and Monetary Fundamentals: What Do We Learn from Long-Horizon Regressions?,” *Journal of Applied Econometrics*, September/October 1999, 14 (5), 491–510.
- Kogan, Leonid**, “Asset Prices and Real Investment,” *Journal of Financial Economics*, September 2004, 73 (4), 411–431.
- and **Dimitris Papanikolaou**, “Firm Characteristics and Stock Returns: The Role of Investment-Specific Shocks,” *Review of Financial Studies*, 2013. Forthcoming.
- and —, “Growth Opportunities, Technology Shocks and Asset Prices,” *The Journal of Finance*, 2013. Forthcoming.
- , —, **Amit Seru, and Noah Stoffman**, “Technological Innovation, Resource Allocation, and Growth,” 2012. Working paper.
- , —, and **Noah Stoffman**, “Technological Innovation: Winners and Losers,” 2013. Working paper.
- Kung, Howard and Lukas Schmid**, “Innovation, Growth, and Asset Prices,” April 2012. Working paper.
- Li, Wendy C. Y.**, “Depreciation of Business R&D Capital,” Technical Report, Bureau of Economic Analysis October 2012. R&D Satellite Account Paper.
- Loualiche, Erik**, “Asset Pricing with Entry and Imperfect Competition,” 2013. Working Paper.
- Lustig, Hanno, Stijn Van Nieuwerburgh, and Adrien Verdelhan**, “The Wealth-Consumption Ratio,” *The Review of Asset Pricing Studies*, 2013, 3 (1), 38–94.
- Moore, Gordon E.**, “No Exponential is Forever: But Forever can be Delayed!,” in “Solid-State Circuits Conference,” Vol. 1 of *Digest of Technical Papers* 2003, pp. 20–23.

- Newey, Whitney K. and Kenneth D. West**, “A Simple, Positive Semi-definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix,” *Econometrica*, May 1987, *55* (3), 703–708.
- Novy-Marx, Robert**, “An Equilibrium Model of Investment Under Uncertainty,” *The Review of Financial Studies*, 2007, *20* (5), 1461–1502.
- Oberfield, Ezra**, “Business Networks, Production Chains, and Productivity: A Theory of Input-Output Architecture,” January 2013. Working paper.
- Ofek, Eli and Matthew Richardson**, “DotCom Mania: The Rise and Fall of Internet Stock Prices,” *The Journal of Finance*, June 2003, *58* (3), 1113–1138.
- Opp, Christian C.**, “Cycles of Innovation and Financial Propagation,” January 2010. Working paper.
- Papanikolaou, Dimitris**, “Investment Shocks and Asset Prices,” *Journal of Political Economy*, October 2011, *119* (4), 639–685.
- Pástor, Ľuboš and Pietro Veronesi**, “Was There a NASDAQ Bubble in the Late 1990s?,” *Journal of Financial Economics*, July 2006, *81* (1), 61–100.
- and — , “Technological Revolutions and Stock Prices,” *The American Economic Review*, September 2009, *99* (4), 1451–1483.
- Rauh, Joshua D. and Amir Sufi**, “Explaining Corporate Capital Structure: Product Markets, Leases, and Asset Similarity,” *Review of Finance*, 2012, *16* (1), 115–155.
- Rebelo, Sergio**, “Long-Run Policy Analysis and Long-Run Growth,” *The Journal of Political Economy*, 1991, *99* (3), 500–521.
- Romer, Paul M.**, “Endogenous Technological Change,” *Journal of Political Economy*, 1990, *98* (5), S71–S102.
- Schmitt-Grohe, S. and M. Uribe**, “Solving Dynamic General Equilibrium Models Using a Second-Order Approximation to the Policy Function,” *Journal of Economic Dynamics and Control*, 2004, *28*, 755–775.
- Shapiro, Carl and Hal R. Varian**, *Information Rules: A Strategic Guide to the Network Economy*, Harvard Business School Press, 1999.
- Stambaugh, Robert F.**, “Predictive Regressions,” *Journal of Financial Economics*, 1999, *54* (1), 375–421.
- van Binsbergen, Jules H. and Ralph S. J. Koijen**, “Predictive Regressions: A Present-Value Approach,” *The Journal of Finance*, August 2010, *65* (4), 1439–1471.
- Weil, Phillippe**, “The Equity Premium Puzzle and the Risk-free Rate Puzzle,” *Journal of Monetary Economics*, November 1989, *24* (3), 401–421.
- Zhang, Lu**, “The Value Premium,” *The Journal of Finance*, February 2005, *60* (1), 67–103.

**Table 1: TFP-forecasting regressions I**

The regression equation is  $TFP_{t \rightarrow t+h} = a + b \times PD_t^{IT} + \epsilon_{t \rightarrow t+h}$ . The dependent variable  $TFP_{t \rightarrow t+h}$  is the utilization-adjusted TFP measure provided by the San Francisco Federal Reserve, which is a percentage change (quarterly log change times 100). The independent variable is the IT sector's price-dividend ratio adjusted for repurchases. Data are quarterly over 1971Q1–2012Q4. Panel A's  $t$ -statistics use the Hodrick (1992) correction equal to the forecast horizon length.  $\sigma(\mathbb{E}[TFP])$  is the standard deviation of the fitted value:  $\sigma(\hat{b} \times PD_t^{IT})$ . Panel B reports the  $t$ -statistics calculated under Newey and West (1987) ( $t_{NW}$ ), and a Monte Carlo bootstrap method ( $t_{MC}$ ), developed by Kilian (1999) and used in Goyal and Welch (2008). I also report an adjusted R-squared for the Monte Carlo bootstrap under  $\bar{R}_{MC}^2$  (with Hodrick (1992) standard errors). Data sources and definitions for the IT sector are detailed in Appendix B.

<b>Panel A</b>				
Horizon $h$	$b$	$t(b)$	$\bar{R}^2$	$\sigma(\mathbb{E}[TFP])$
1 year	0.01	1.0	0.08	0.45
2 year	0.03	2.1	0.21	0.97
3 year	0.04	3.4	0.39	1.56
4 year	0.05	4.7	0.48	1.97
5 year	0.06	4.9	0.48	2.23
<b>Panel B</b>				
Horizon $h$	$b$	$t_{NW}(b)$	$t_{MC}(b)$	$\bar{R}_{MC}^2$
1 year	0.01	2.5	0.7	0.03
2 year	0.03	4.1	1.5	0.17
3 year	0.04	3.4	2.3	0.34
4 year	0.05	6.7	2.8	0.43
5 year	0.06	6.7	3.3	0.43

**Table 2: TFP-forecasting regressions II**

The regression equation is  $TFP_{t \rightarrow t+h} = a + b_{IT} \times PD_t^{IT} + b_{IND} \times PD_t^{IND} + \epsilon_{t \rightarrow t+h}$ . The dependent variables are the standard TFP measure (“TFP”) and the utilization-adjusted TFP measure (“Adjusted TFP”), both of which are provided by the San Francisco Federal Reserve and are in percentage change (quarterly log change times 100). The independent variables are the repurchase-adjusted price-dividend ratios for the IT sector and the industrial sector. Data are quarterly over 1971Q1–2012Q4. Standard errors use the Hodrick (1992) correction equal to the forecast horizon length.  $t$ -statistics are in parentheses. Data sources and definitions are detailed in Appendix B.

Horizon $h$	Statistic	TFP			Adjusted TFP		
		(1)	(2)	(3)	(1)	(2)	(3)
1 year	$b_{IT}$	0.01		0.00	0.01		0.01
	$t(b_{IT})$	(0.30)		-(0.03)	(1.00)		(0.44)
	$b_{IND}$		0.04	0.04		0.06	0.04
	$t(b_{IND})$		(0.50)	(0.56)		(1.20)	(0.50)
	$\bar{R}^2$	<i>0.01</i>	<i>0.02</i>	<i>0.02</i>	<i>0.08</i>	<i>0.08</i>	<i>0.10</i>
2 year	$b_{IT}$	0.01		0.01	0.03		0.02
	$t(b_{IT})$	(0.60)		(0.23)	(2.10)**		(0.89)
	$b_{IND}$		0.08	0.06		0.12	0.07
	$t(b_{IND})$		(0.80)	(0.54)		(1.80)*	(0.59)
	$\bar{R}^2$	<i>0.03</i>	<i>0.05</i>	<i>0.04</i>	<i>0.21</i>	<i>0.19</i>	<i>0.24</i>
3 year	$b_{IT}$	0.03		0.02	0.04		0.03
	$t(b_{IT})$	(1.40)		(0.83)	(3.40)***		(1.89)*
	$b_{IND}$		0.12	0.05		0.18	0.07
	$t(b_{IND})$		(1.20)	(0.38)		(2.20)**	(0.65)
	$\bar{R}^2$	<i>0.11</i>	<i>0.08</i>	<i>0.11</i>	<i>0.39</i>	<i>0.28</i>	<i>0.42</i>
4 year	$b_{IT}$	0.05		0.04	0.05		0.04
	$t(b_{IT})$	(2.90)***		(2.34)***	(4.70)***		(3.46)***
	$b_{IND}$		0.17	0.03		0.21	0.07
	$t(b_{IND})$		(1.70)*	(0.26)		(2.20)**	(0.76)
	$\bar{R}^2$	<i>0.30</i>	<i>0.15</i>	<i>0.30</i>	<i>0.48</i>	<i>0.31</i>	<i>0.50</i>
5 year	$b_{IT}$	0.06		0.05	0.06		0.06
	$t(b_{IT})$	(4.30)***		(4.16)***	(4.90)***		(4.10)***
	$b_{IND}$		0.20	0.05		0.21	0.05
	$t(b_{IND})$		(1.80)*	(0.43)		(2.10)**	(0.52)
	$\bar{R}^2$	<i>0.38</i>	<i>0.20</i>	<i>0.38</i>	<i>0.48</i>	<i>0.25</i>	<i>0.48</i>

\*\*\* -  $p < 0.01$ , \*\* -  $p < 0.05$ , \* -  $p < 0.1$

**Table 3: TFP-forecasting regressions III**

The regression equation is  $TFP_{t \rightarrow t+h} = a + b_{IT} \times PD_t^{IT} + b_{IND} \times PD_t^{IND} + \epsilon_{t \rightarrow t+h}$ . The dependent variable  $TFP_{t \rightarrow t+h}$  is the utilization-adjusted TFP measure provided by the San Francisco Federal Reserve, which is a percentage change (quarterly log change times 100). The independent variables are the repurchase-adjusted price-dividend ratios for the IT sector and the industrial sector. Data are quarterly, and over various subperiods that are marked. Standard errors use the Hodrick (1992) correction equal to the forecast horizon length.  $t$ -statistics are in parentheses.  $\sigma(\mathbb{E}[TFP])$  is the standard deviation of the fitted value:  $\sigma(\hat{b} \times PD_t^{IT})$ . Data sources and definitions are detailed in Appendix B.

<b>Panel A: 1971Q1 – 1986Q4</b>				
	$b$	$t(b)$	$\bar{R}^2$	$\sigma(\mathbb{E}[TFP])$
1 year	0.01	1.3	0.06	0.47
3 year	0.05	3.0	0.37	1.71
5 year	0.05	4.5	0.39	2.05
<b>Panel B: 1986Q4 – 2002Q3</b>				
	$b$	$t(b)$	$\bar{R}^2$	$\sigma(\mathbb{E}[TFP])$
1 year	0.01	2.2	0.09	0.38
3 year	0.04	4.0	0.30	1.02
5 year	0.05	5.7	0.41	1.52
<b>Panel C: 2002Q3 – 2012Q4</b>				
	$b$	$t(b)$	$\bar{R}^2$	$\sigma(\mathbb{E}[TFP])$
1 year	0.05	2.3	0.15	0.66
3 year	0.06	2.2	0.14	0.88
5 year	0.05	6.4	0.35	0.81

Table 4: Calibration and point estimates (quarterly)

Parameter	Value	Description	Source/Target
<i>Household</i>			
$\beta$	0.9915	Subjective discount factor	Match levels of PD ratios
$\psi$	0.9	Elasticity of intertemporal substitution	Match $\beta$ risk exposures and growth rates
$\gamma$	10	Coefficient of relative risk aversion	Match risk premia
<i>Industrial</i>			
$\alpha$	0.3	Non-IT capital share of factor income	Literature
$\delta$	0.02	Capital depreciation rate	Literature
$\zeta$	1.01	Adjustment cost parameter	Literature
$\rho$	0.9945	Exogenous TFP persistence	Match macro autocorrelation
$\sigma_\epsilon$	0.0175	Productivity volatility	Match macro volatility
<i>IT</i>			
$\bar{\theta}$	1.66	Scale parameter	SMM estimates
$\mu - 1$	0.134	IT net markup	Compustat, Goeree (2008)
$\phi$	0.945	IT good/firm survival rate	Compustat (default), BEA (depreciation), Li (2012)
$\eta_s$	0.834	Elasticity of new IT goods wrt R&D	CRSP/Compustat (PD), SF Fed (TFP), Griliches (1990)
$\eta_k$	-0.242	Capital reallocation friction	Match transition path, PD ratio transitions, growth rates

**Table 5: IT sector markups**

This table reports average markups of IT firms over the annual period 1974–2012. Markups are estimated by  $\mu = \frac{1}{1-x} - 1$ , where  $x$  is the EBITDA-sales ratio, defined below. The row “Aggregate” refers to the sum of EBITDA divided by the sum of sales, and then temporally estimates the average value. The row “Cross section” takes the cross-sectional median of all firms in every year, and then temporally estimates the average value. Standard errors have the Newey-West (1987) adjustment with three lags. Data are defined in Appendix B.

	Lower 95%	Estimate	Upper 95%
Aggregate	0.138	0.142	0.145
Cross-section	0.089	0.093	0.098

**Table 6: Estimates of  $\eta_s$** 

This table estimates the parameter  $\eta_s$  from the data by running the following regression:  $TFP_{t \rightarrow t+h} = a + b \log PD_t^{IT} + \epsilon_{t+h}$ . The dependent variable  $TFP_{t \rightarrow t+h}$  is the utilization-adjusted TFP measure provided by the San Francisco Federal Reserve, which is a percentage change (quarterly log change times 100). The independent variable is the (log) price-dividend ratio for the IT sector, which is adjusted for repurchases. Data are quarterly, from 1974Q1–2012Q4. The model counterpart is  $\log(Z_{t+1}/Z_t) = (\rho - 1) \log A_t + \frac{\eta_s}{1-\eta_s} \log \mathbb{E}_t[M_{t+1}V_{t+1}] + \epsilon_{t+1}$ . The parameter  $\hat{\eta}_s$  is retrieved from the estimate of  $\hat{b}$  by the equation:  $\eta_s(b) = \frac{b}{1+b}$ . Ninety-five percent confidence intervals are constructed using the delta method:  $se(\hat{\eta}) = \eta'_s(\hat{b}) \left[ se(\hat{b}) \right]^2 \eta'_s(\hat{b})$ , where  $se(\hat{b})$  is computed with the Newey-West (1987) adjustment with three lags. Data are described in Appendix B.

	Lower 95%	$\hat{\eta}_s$	Upper 95%	$\bar{R}^2$
1 year	0.35	0.46	0.56	0.08
2 year	0.53	0.65	0.78	0.21
3 year	0.64	0.75	0.86	0.39
4 year	0.69	0.79	0.90	0.48
5 year	0.72	0.82	0.93	0.50

**Table 7: Model and data macroeconomic statistics**

This table reports macroeconomic growth and volatility statistics generated by the steady state of the model and compares them to the data. The model is simulated on a quarterly basis and then time-aggregated to an annual one. The steady state are for time periods  $s > \tilde{T}$ , where  $\tilde{T}$  is defined in (22). Data statistics are calculated from Bureau of Economic Analysis’s data over the annual period 1974–2012. In the model, total investment,  $INV$ , is the sum of capital investment, IT investment, and research expenditure; in the data, total investment is real, nonresidential, fixed, private investment.  $\Delta x$  is the log-difference of the variable  $x$ . Data sources are discussed in Appendix B.

Statistic	Data	Model
<i>Consumption growth</i>		
mean( $\Delta c$ )	2.00	1.79
std( $\Delta c$ )	2.27	2.38
AC1( $\Delta c$ )	0.39	0.40
<i>Business cycle</i>		
$\sigma_{\Delta c}/\sigma_{\Delta y}$	0.61	0.96
$\sigma_{\Delta INV}/\sigma_{\Delta c}$	4.38	3.07

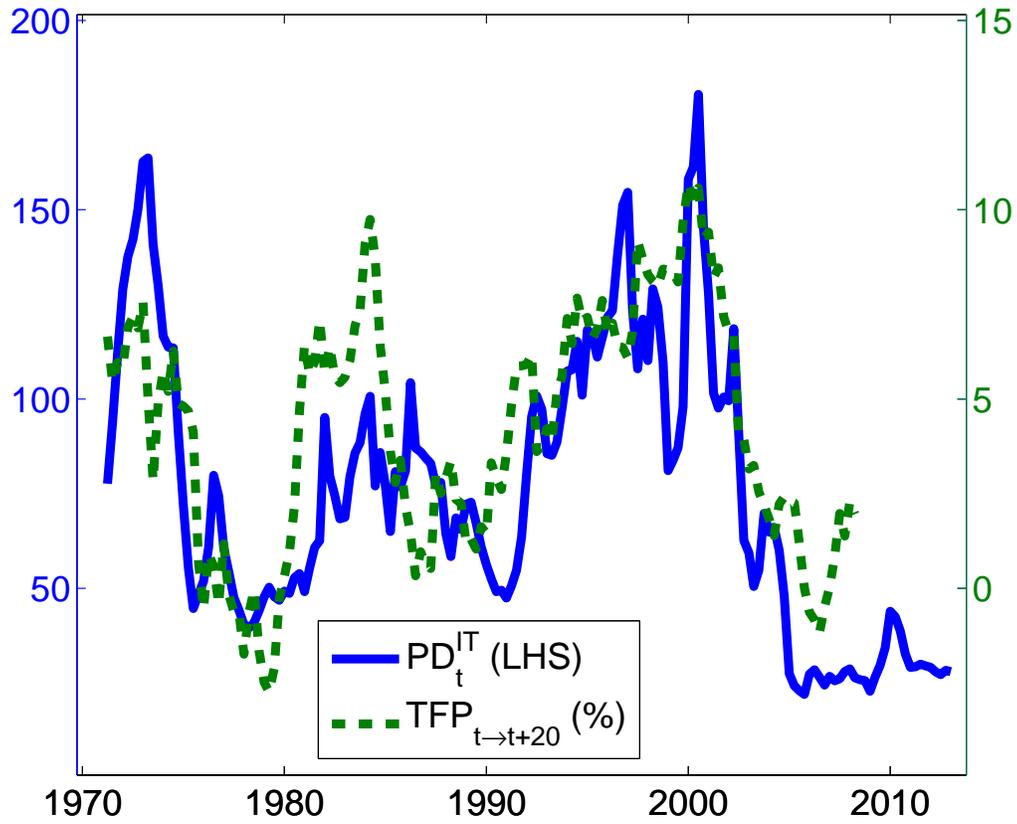
**Table 8: Asset pricing moments**

Panel A reports the model’s annualized moments. Equity premia include a leverage adjustment: with constant financial leverage, the levered equity premium is  $\mathbb{E}[r_i^{\text{LEV}} - r_f] \doteq \mathbb{E}[r_i - r_f](1 + \overline{D/E})$ , where  $\overline{D/E}$  is the average debt-equity ratio, which is set to one to be consistent with firm-level data (Rauh and Sufi (2012)) for industrial firms, and is set to 0.36 for IT firms to match my estimate of the sector’s average debt-equity ratio in Compustat. Volatility is also scaled by the same leverage factors. Panel B reports my estimates of the data’s annual moments. Returns are value-weighted, monthly from the period 1971 until 2012, and deflated by the consumer price index. The portfolio strategy would be to buy firms at their post-IPO price at month-end and sell them at the delisting price, if occurring. All numbers are in percent except the Sharpe ratios.

<b>Panel A: Model</b>			
	Mean	Stdev	Sharpe ratio
$\mathbb{E}[r_f]$	3.86	0.8	0
$\mathbb{E}[r_{IND}]$	7.46	4.36	0.88
$\mathbb{E}[r_{IT}]$	4.39	3.46	0.21
$\mathbb{E}[r_{MKT}]$	6.46	5.40	0.51
<b>Panel B: Data</b>			
	Mean	Stdev	Sharpe ratio
$\mathbb{E}[r_f]$	1.49	0.9	0
$\mathbb{E}[r_{IND}]$	6.44	15.5	0.38
$\mathbb{E}[r_{IT}]$	5.40	28.3	0.27
$\mathbb{E}[r_{MKT}]$	6.00	16.1	0.34

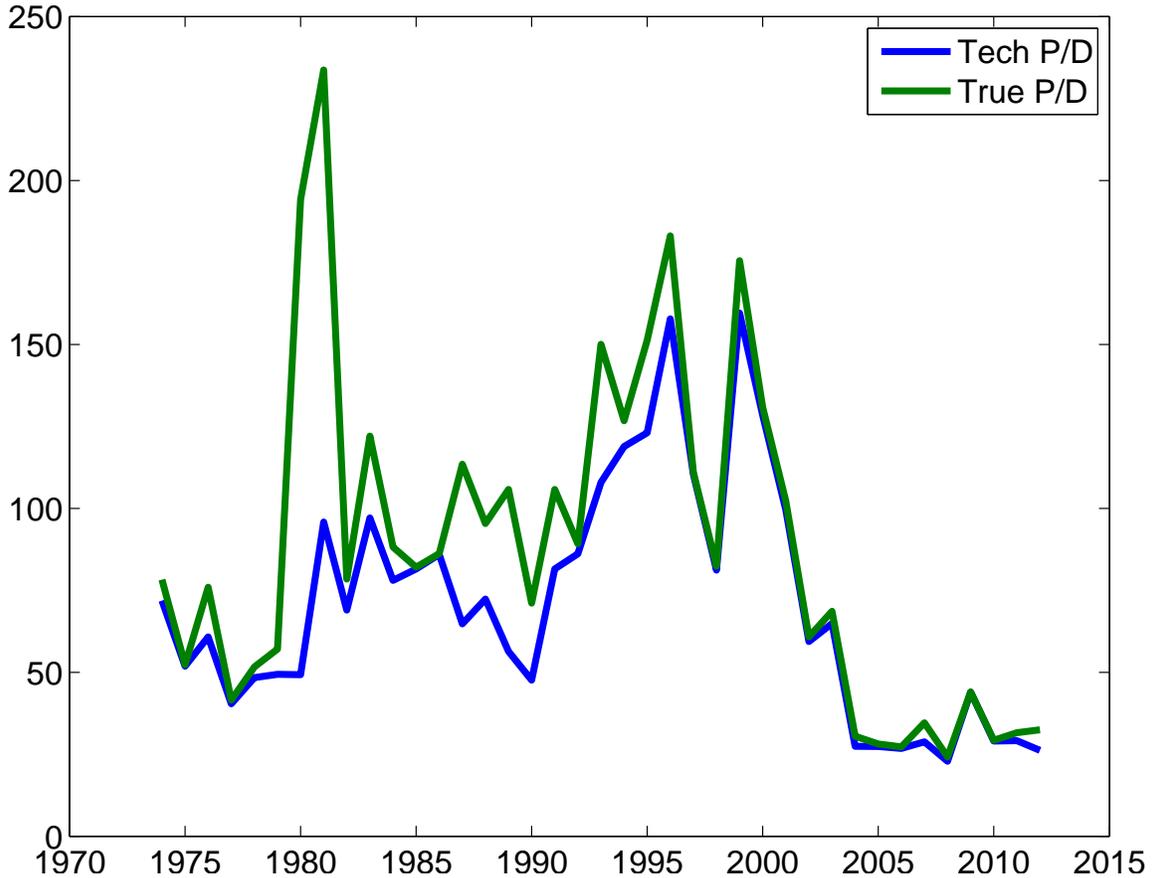
**Figure 1: Five-year TFP growth v  $PD_t^{IT}$**

The process in blue is  $TFP_{t \rightarrow t+20}$ , the five-year cumulative growth of utilization-adjusted TFP measure provided by the San Francisco Federal Reserve, which is a percentage change (quarterly log change times 100). The process in dashed-green is the IT sector's price-dividend ratio adjusted for repurchases. Data are quarterly, from 1974Q1–2012Q4. Data sources and definitions are detailed in Appendix B.



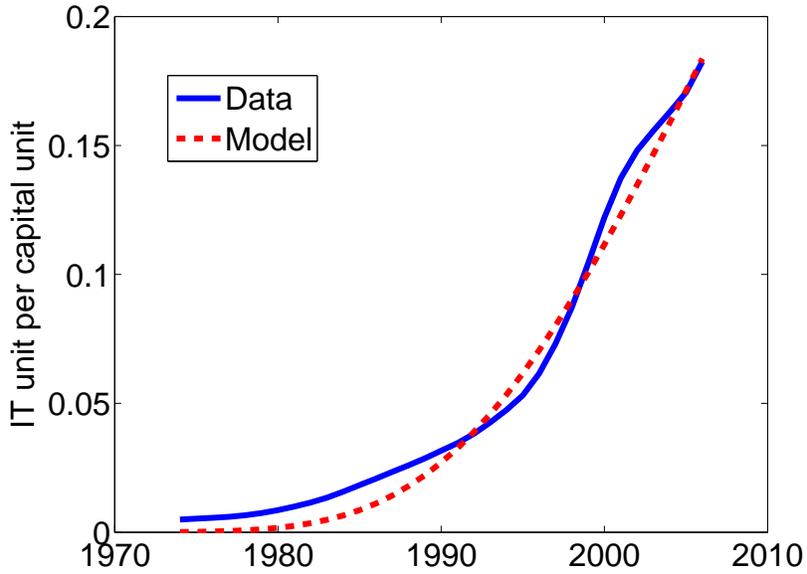
**Figure 2: Market value of IPO firms to incumbents' market value**

This figure plots the relative market values of private firms, proxied by the value of IPOs, to that of incumbents. “Tech P/D” is the annualized price-dividend ratio of the IT sector at year-end, which has been adjusted for repurchases. “True P/D” comes from the formula:  $P/D_{True} = \frac{MV_{public}}{MV_{public}+MV_{private}} \times P/D_{Tech} + \frac{MV_{private}}{MV_{public}+MV_{private}} \times P/D_{Private}$ .  $P/D_{Private}$  comes from the value-weighted price-dividend ratios of all new IPO firms in the IT sector in the year, which has been adjusted for repurchases. Data sources and definitions are detailed in Appendix B.



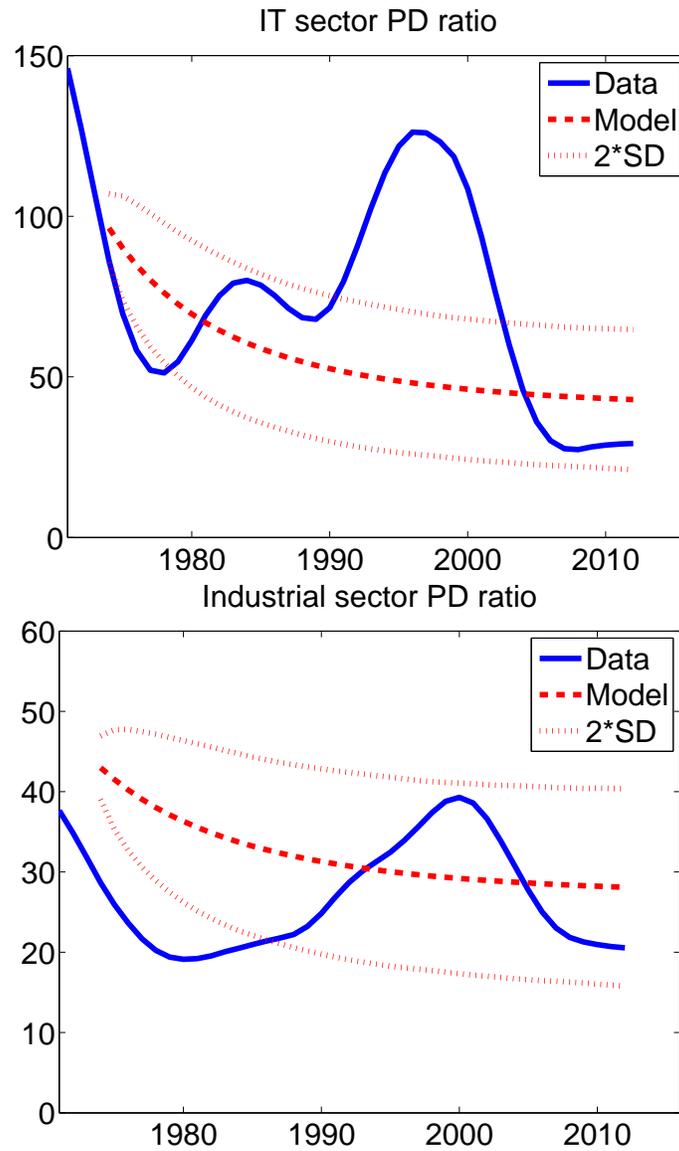
**Figure 3: Time series of IT-capital ratio**

This figure plots the IT-capital ratio, the ratio of the IT sector's quantity of capital services to the industrial sector's in solid blue. Capital services are direct estimates of factor income which are based on flows derived from constructed constant-quality capital stock indices. The IT sector is defined as the sum of software, hardware, and communications as listed in the Bureau of Economic Analysis; the industrial sector comprises the remaining 62 asset classes. See Jorgenson and Stiroh (2000) for details. A detailed description of the origin of the data for this figure is in Appendix B. I fix an initial IT-capital ratio  $\frac{N_0 X_0}{K_0} < \lim_{t \rightarrow \infty} \mathbb{E} \left[ \frac{N_t X_t}{K_t} \right]$  and calibrate the model's average simulation path (in dashed red) to match the length and curve of the data.



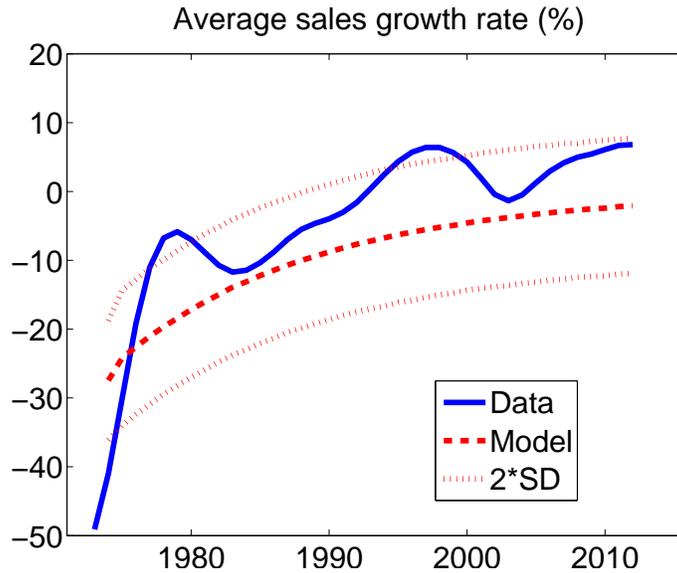
**Figure 4: Time series of price-dividend ratios**

This figure plots time series paths of the sectors' price-dividend ratios. The dashed line is the model's average simulation path. The dotted lines are two times the model's standard deviation of point estimates across simulations. The solid blue line is data. The top figure is the IT sector; the bottom is the industrial sector. In the data, I calculate repurchase-adjusted price-dividend ratios, as described in Appendix B. Data are quarterly and are smoothed with a Hodrick-Prescott filter with a smoothing parameter equal to 1600.



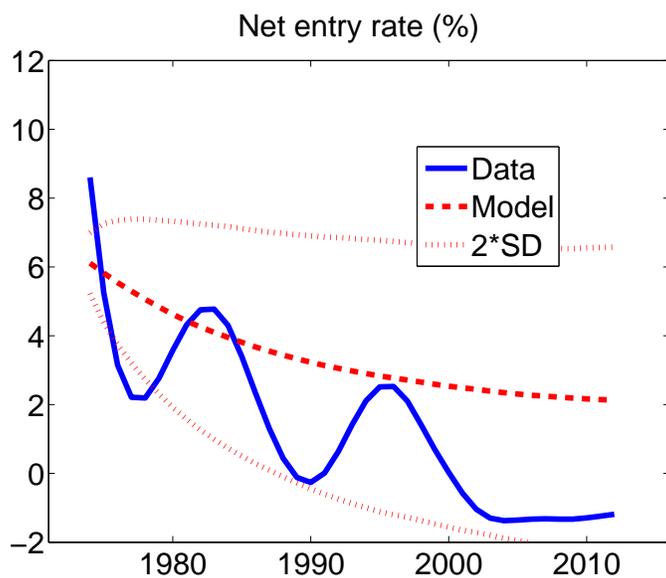
**Figure 5: IT sector's average sales growth rate over time**

This figure plots the average sales growth rate per firm of the IT sector. The dashed line is the model's average simulation path. In the model, the variable is  $\log\left(\frac{\Pi_{t+1}}{\Pi_t}\right)$ . The dotted lines are two times the model's standard deviation of point estimates across simulations. The solid line is data. The data use Compustat data for the IT sector to calculate aggregate sales growth rates per public IT firm ( $N_t$ ):  $\log\left(\frac{y_{t+1}}{y_t}\right)$ , where  $y_t = \frac{\sum_i^{N_t} Sales_{i,t}}{N_t}$ . Data are quarterly and are smoothed with a Hodrick-Prescott filter with a smoothing parameter equal to 1600. IT firms are identified by NAICS codes in Appendix B.



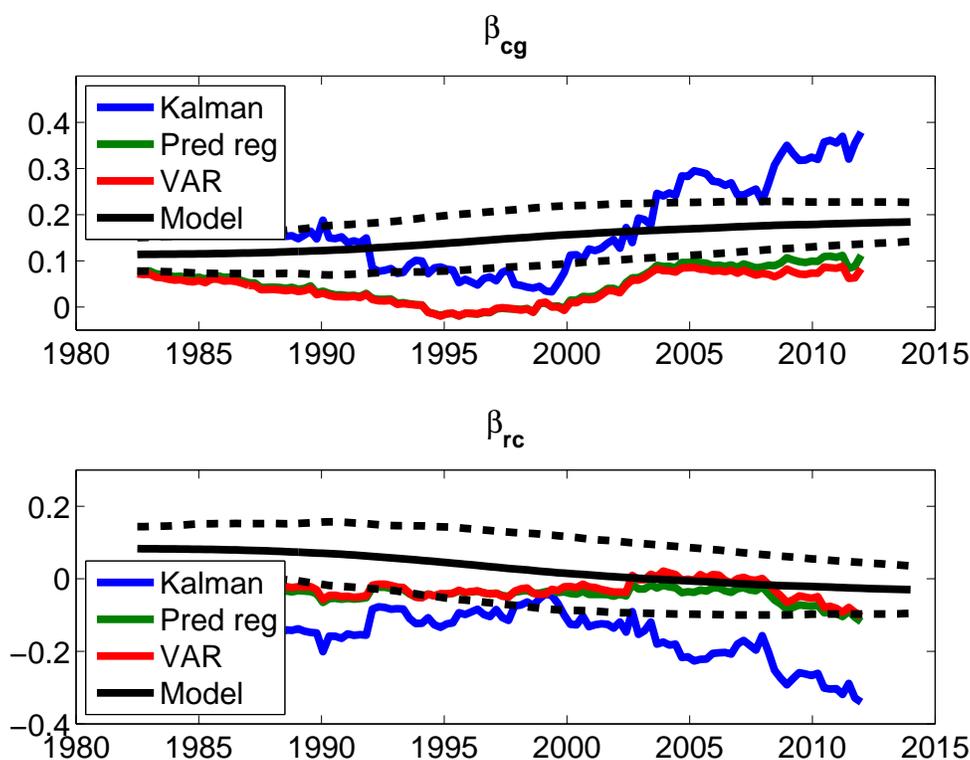
**Figure 6: IT sector's firm-count growth rate over time**

This figure plots the net entry rate of the IT sector. The dashed line is the model's average simulation path. In the model, the variable is  $\log\left(\frac{N_{t+1}}{N_t}\right)$ . The dotted lines are two times the model's standard errors. Standard errors are estimated from the standard deviation of point estimates across simulations. Ten-thousand simulations are run. The solid line is data. The data use the two-year compound annual growth rate of the growth rate of public IT firms. Data are quarterly and are smoothed with a Hodrick-Prescott filter with a smoothing parameter equal to 1600. IT firms are identified by NAICS codes described in Appendix B.



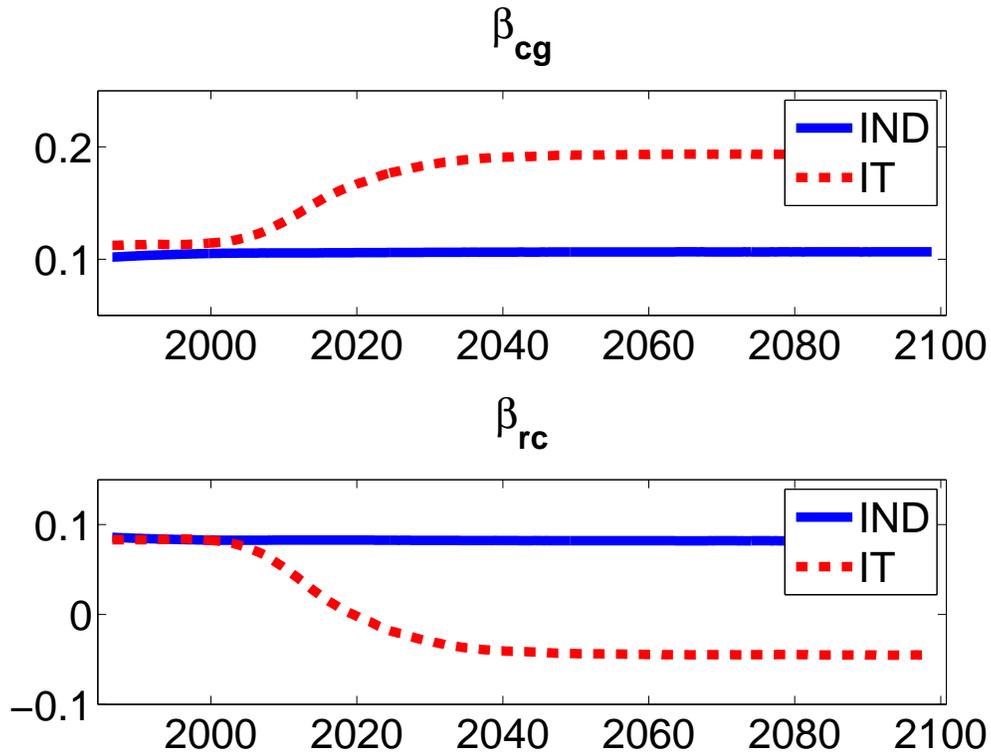
**Figure 7: Rolling risk exposures I: 1974-2012 sample**

The form of the regression is  $r_{IT,t} = a_{IT} + \beta_{IT,cg} \times g_{C,t} + \beta_{IT,rc} \times r_{C,t} + \nu_t$ . The risk factors,  $g_{C,t}$  and  $r_{C,t}$ , are standardized. Returns are real. The regressions are rolling and each regression includes 50 quarters of data. The dotted lines are two times the model's standard deviation of point estimates across simulations. Three data series are plotted, depending on how the long-run expected consumption growth of the data was estimated: "Kalman", uses a Kalman filter; "Pred reg" uses a predictive regression; "VAR" uses a vector autoregression. Data estimation details are provided in Section C. Model estimation details are provided in 4.



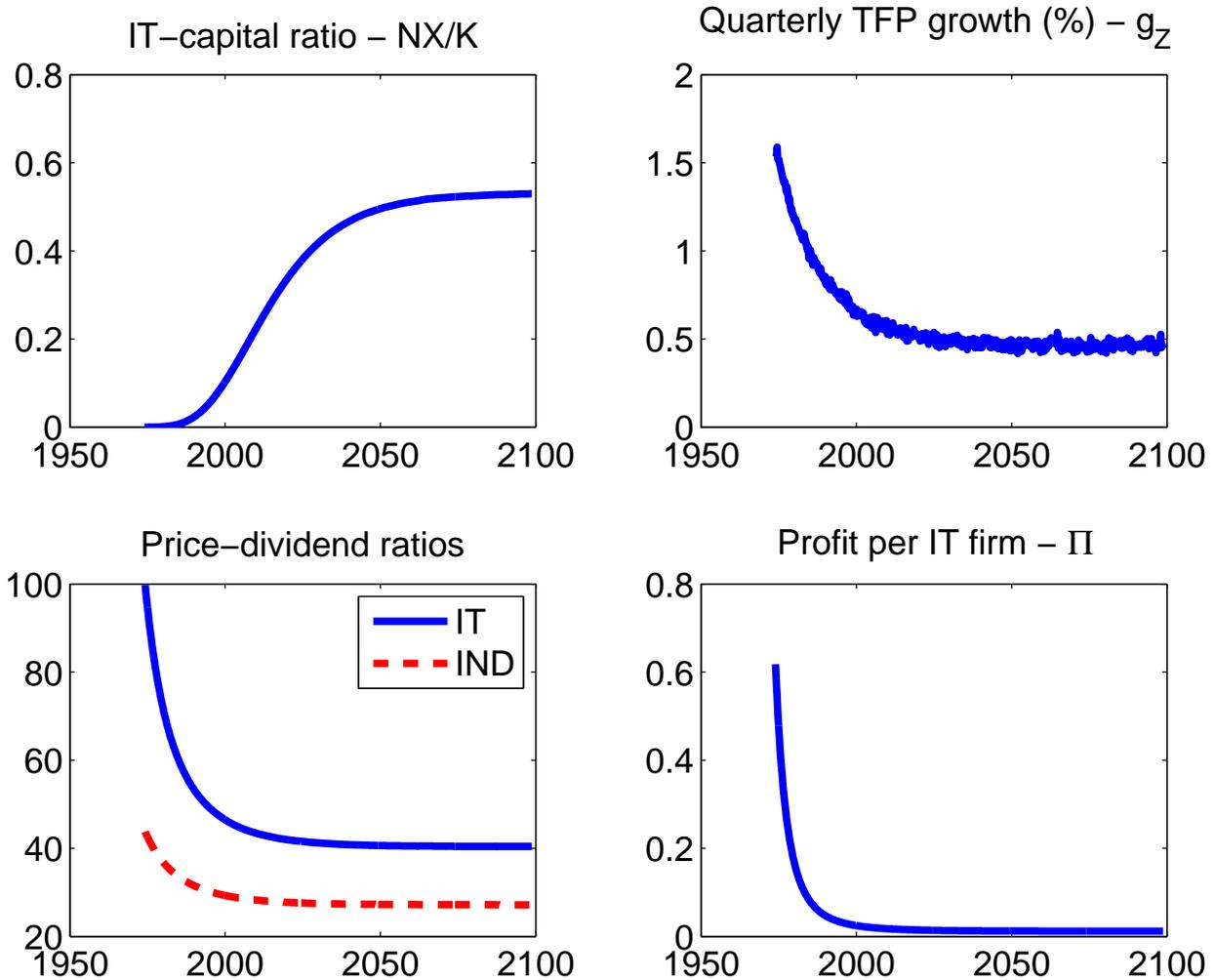
**Figure 8: Rolling risk exposures II: Full sample paths**

The form of the regression is  $r_{i,t} = a_i + \beta_{i,cg} \times g_{C,t} + \beta_{i,rc} \times r_{C,t} + \nu_t$ , where  $i$  indexes the IT and industrial sector. The regressions are rolling and each regression includes 50 quarters of data. The risk factors,  $g_{C,t}$  and  $r_{C,t}$ , are standardized in both the model and the data. Returns are real. Model estimation details are provided in Section 4.



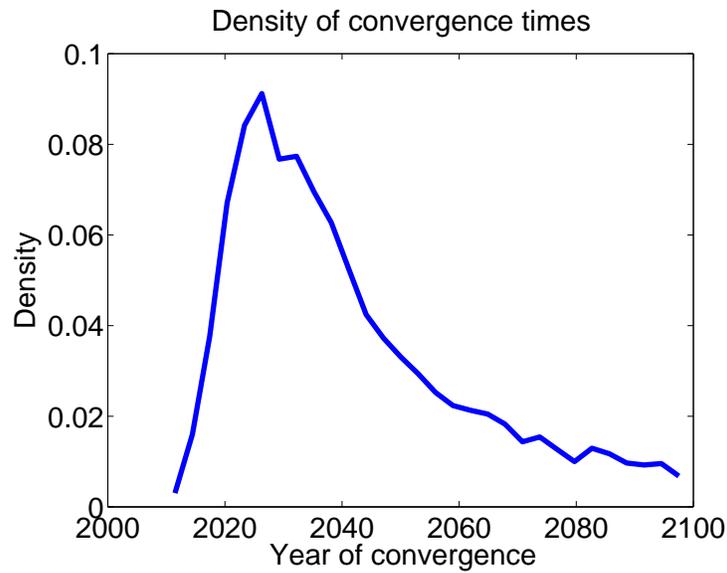
**Figure 9: Full transition sample paths**

The top-left panel plots the IT-capital ratio. The top-right panel plots the quarterly growth rate in measured TFP. The bottom-right panel plots profits made by each IT good producer. The bottom-left panel plots the price-dividend ratios of the IT sector and the industrial sector. The figures below show the average across simulations.



**Figure 10: Density of convergence times**

This figure plots the density of convergence times, as described in Section 4 under the model being simulated with the parameter vector  $\hat{\beta}$ , as described in (18). The convergence time is defined as  $T \doteq \inf \left\{ t : \frac{N_t X_t}{K_t} \geq \lim_{t \rightarrow \infty} \mathbb{E} \left[ \frac{N_t X_t}{K_t} \right] \right\}$ . The model is simulated 25,000 times with the same  $\hat{\beta}$  to obtain the density.



**Figure 11: Model: Densities of TFP growth per year**

This figure plots the density of productivity growth per year. The top figure plots the historical amount in the model over the simulated period 1974–2013. The actual amount observed in the data was 0.87 percent TFP growth per year. The bottom figure generates the future TFP growth from 2013 until the stopping time  $T$  is reached. Both cumulative growth rates are divided by the number of years. The figures plot the entire density of all the 25,000 simulations under the estimated parameter vector  $\hat{\beta}$ . Further details are provided in Section 4.

