Levered Ideas: Risk Premia along the Credit Cycle*

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Abstract

We quantitatively evaluate a general equilibrium model in which the endogenous supply of collateral drives the joint dynamics of credit, risk and risk premia. Endogenous adoption facilitates the transformation of intangible ideas into technology that productive firms can borrow against. In the model, the arrival of new technologies drives the ratio between ideas and collateralizable capital (IC ratio) which is a significant predictor of leverage and returns in stock and corporate bond markets. In particular, a high IC ratio predicts an endogenously high market price of risk and high unlevered returns to technology adoption, while a low IC ratio comes with a low equilibrium market price of risk but high levered returns. Interpreted in the context of venture capitalists (adopters) and buyout funds (levered firms), the model rationalizes repeated, but distinct, venture capital and buyout waves, and returns. VC waves occur when the equilibrium price of risk is elevated, while buyout volume spikes when credit risk premia are endogenously low. Quantitatively, our model of a credit cycle driven by the slow transformation of new ideas into collateralizable assets gives rise to predictability in stock and corporate bond markets. Empirically, we document evidence that innovation measures forecast aggregate leverage, credit spreads and credit risk premia, as well as buyout activity, supportive of the model predictions.

Keywords: Technology adoption, innovation, collateral, leverage, credit cycle, credit spreads, predictability, risk premia, venture capital, buyout

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1 Introduction

It is hard to borrow against an idea or the mere prospects of future profits. Indeed, often lenders require collateral to secure loans, tangible assets ideally, and in the absence of those, charge substantially higher spreads on unsecured debt. Yet, many of the great technological innovations started as just that - ideas. These ideas, through the efforts of innovators and funding of venture capitalists recognizing their growth potential, slowly diffuse through the economy and are adopted by productive firms, eventually boosting growth. That process of adoption not only integrates technological innovation into the production process, but also creates assets that firms can borrow against, collateral that is, and raises the economy's debt capacity.

In this paper, we examine a model of a credit cycle driven by the slow transformation of new ideas into collateralizable assets through adoption. More specifically, ours is a general equilibrium model with a representative agent and a rich production sector, in which new ideas or blueprints exogenously arrive and move the stochastic technology frontier. Before these innovations are available for productive and collateral use by levered firms that are subject to standard neutral productivity shocks, specialized agents that we refer to as adopters need to fund their transformation to collaterizable assets. That transformation is risky, and risk-sensitive agents need to be compensated for that exposure. Similarly, once adopted, productive firms exploit the additional collateral to take advantage of the preferential tax treatment of defaultable debt by levering up, thereby increasing their expsoure to aggregate risk. A key feature of our model is that the endogenous supply of collateral drives the joint dynamics of credit, risk and risk premia along the credit cycle.

We find it convenient to summarize key aspects of the credit cycle by one endogenous state variable, namely the ratio of ideas to collateralizable capital, the IC ratio henceforth. When new ideas are abundant, so that the IC ratio is high, expected returns to adoption are high, while aggregate leverage and collateral are low. In turn, a low IC ratio coincides with episodes with ample collateral, making leverage cheap, thus raising expected returns to levered capital. Importantly, the ratio IC emerges as a significant predictor of expected returns not only of adoption and levered stock returns, but also corporate bond returns along the credit cycle.

Quantitatively, our model replicates not only realistic average levered excess stock returns, but also time variation in expected returns, even though it is driven by two sources of homoskedastic risk, namely shocks to ideas and neutral technology. In our model, the market price of risk, namely the conditional volatility of the stochastic discount factor, fluctuates endogenously with the IC ratio. In particular, after positive news to growth potential and the IC ratio, the market price of risk rises along with the expected returns to adoption. Conversely, when the IC ratio falls and leverage goes up, the equilibrium market price of risk falls, but higher expected stock returns reflect elevated exposure due to leverage rather than risk pricing. Intriguingly, in the model, the IC ratio forecasts not only stock, but also corporate bond risk premia, and leverage ratios. Quantitatively, these results depend on our assumption that the representative agent has Epstein-Zin preferences, so that the rise in the market price of risk after a revision in growth expectations is due to elevated uncertainty about future growth, while the conditional volatility of consumption falls.

As an indicator of the credit cyle, the IC ratio predicts movements in credit markets. Indeed, in the model it forecasts lower credit spreads as well as lower credit risk premia going forward. In this sense, it suggests that debt will be relatively cheap in the future, so that leverage will be high. Using the number of patent applications as an empirical proxy for the mass of blueprints in the model and aggregate capital as a measure of total collateral, we find evidence supportive of this prediction in the data. Indeed, a temporarily high ratio of patent applications to collateral forecasts lower future credit spreads and corporate bond risk premia, and higher future leverage.

Arguably a natural interpretation of our asset pricing results is in the context of the private equity industry. In this regard, we can view adopters as venture capitalists that fund the risky transformation of promising ideas into marketable products. Most of the funding for early ventures comes in the form of equity injections, consistent with our model and the lack of collateral to facilitate debt financing for that purpose. Our productive firms take advantage of access to collateral to fund the use of new technologies with debt, which perhaps broadly resembles buyout funds using leverage to increase the productivity of their portfolio companies. While our model clearly does not speak to the organizational form of private equity, nevertheless, under this interpretation, flows into venture capital occur when the IC ratio and thus the market price of risk are high, so that (unlevered) expected returns to adoption are high. Empirically, indeed, the tech boom of the late 1990's when VC flourished coincided with a surge of the VIX, for example. Buyout waves, in turn, do not occur simultaneously but at a later stage of the credit cycle, when there is ample collateral and spreads on defaultable debt relatively low, so that debt is relatively cheap. Incidentally, the model predicts that in such episodes the market price of risk is relatively low, so that high expected returns on buyout funds mostly reflect leverage and expected productivity increases. Coincidentally, during the buyout booms of the mid 2000's, both the VIX and measures of credit risk premia, such as the Gilchrist Zakrajsek excess bond premium, fell to minimal levels. The model thus predicts distinct venture capital and buyout waves, and returns, that depend on the stage of the credit cycle. Remarkably, we find that in the data, the ratio of patent applications to collateral predicts higher buyout activity in the medium run.

In spite of renewed interest in credit cycles in the aftermath of the great recession, no clear definition of the concept has yet emerged. The notion of a credit cycle entertained here arguably shares a number of features that are commonly associated with cyclical movements in credit. For example, the credit cycles arising here are distinct from ordinary business cycles, and more persistent, as they are driven by slow moving innovations to growth potential, rather than neutral technology shocks. Similarly, credit markets and stock markets follow distinct cycles, as new innovations are capitalized immediately into stocks, but only with adoption lags into credit markets, so that relative valuations may temporarily diverge. Additionally, our model of credit cycles resonates well with the observation that most debt-fueled major recessions in developed countries, such as the recent great recession and the great depression in the US, as well as the long Japanese slump of the 1990s, were preceded by periods of great technological innovation.

Literature Review Our work builds on the literature on the macroeconomic and asset pricing implications of the arrival and adoption of new technologies and interprets it in the context of its implications for capital structure and debt financing. Our model of technology adoption borrows from Comin and Gertler (2006), Comin, Gertler and Santacreu (2009) and Anzoategui, Comin, Gertler and Martinez (2016), but also features similarities to the asset pricing model of Garleanu, Panageas, and Yu (2012). Papanikolaou (2011), Kogan and Papanikolaou (2014) and Kogan, Papanikolaou, and Stoffman (2016) emphasize the role of embodied, investment specific technology shocks in the transformation of new ideas to implementable technologies, but focus on the cross-sectional differences in firm and household benefits from exposure to these shocks. Shocks to innovation and an economy's growth potential are akin to news shocks, as emphasized in Beaudry and Portier (2004) and, interpreted in the context of the long-run risk literature started by Bansal and Yaron (2004), by Croce (2014). Kung and Schmid (2015) connect the long-run risk literature and the technology adoption and endogenous growth literature, in the context of equilibrium asset pricing with production, as in Jermann (1998), Boldrin, Christiano and Fisher (2001), Kaltenbrunner and Lochstoer (2010), Ai, Croce and Li (2013), Loualiche (2014), and Favilukis and Lin (2014), among others.

Our emphasis on the links between technology adoption and the availability of collateral and debt financing is novel, to the best of our knowledge. Our modeling of capital structure and default is based on Gomes, Jermann and Schmid (2016). Related work on defaultable debt in general equilibrium production economies can be found in Gourio (2010), who focuses on disaster risks, Corhay (2016), who examines cross-industry variation in credit spreads, and Gomes and Schmid (2016) and Favilukis, Lin and Zhao (2016), who model rich firm-level heterogeneity, and wage rigidities, respectively. Our paper shares an asset pricing perspective on the credit risk literature with the contributions of Bhamra, Kuehn, and Strebulaev (2010), Chen (2010), and Chen, Collin Dufresne, and Goldstein (2010) .

A few papers, starting with Jermann and Quadrini (2010), have explored the macroeconomic implications of credit shocks, modeled as exogenous disturbances to the pledgeability of firms' assets. Khan and Thomas (2013) extend this analysis in a setting with rich production heterogeneity. Our model is an attempt to identify sources of movements in the availability of collateral in the context of technology adoption. Lopez Salido, Stein, and Zakrajsek (2015) examine the macroeconomic effects of movements in credit markets driven by sentiment, while Greenwood and Hanson (2013) show that such movements have predictive power for corporate bond returns. One interpretation of our innovations in growth potential is in the context of sentiment, and indeed, we show that measures of growth potential indeed forecast corporate bond returns and spreads in the model and in the data.

Regarding our interpretation of the model in the context of the private equity industry, Opp (2016) also examines the role of venture capitalists in the financing of technology adoption, but does not consider the availability of collateral and credit cycles. Empirically, Peters (2016) also links venture capital returns to movements in volatility, an implication shared by our model, while Axelson, Jenkinson, Stromberg and Weisbach (2013) examine the importance of the relative pricing of credit and equity instruments in shaping buyout activity, showing that buyout activity occurs when debt is relatively cheap. Eisenthal, Feldhuetter, and Vig (2016) show that the risk of an impending buyout is priced in corporate bonds. Relatedly, Haddad, Loualiche, and Plosser (2017) document that buyout waves coincide with low aggregate discount rates. These empirical findings are consistent with, and can be interpreted through the lens of our model.

Structure In the next section, we present our model. Section three uses a parameterized version of the model to examine its implications by means of simulations. That section also discusses the link between our model and its interpretation in the context of the private equity industry more closely. Section four then provides some empirical predictions of the model and discusses empirical evidence based on empirical proxies of the main state variables in the model. Section five provides some concluding remarks.

2 Model

In this section, we introduce a general equilibrium model of endogenous technology adoption, in which adopted technologies can serve as collateral for debt financing that enjoys a tax advantage. New ideas for technological innovations arrive exogenously to the economy, and can be converted to assets utilizable in the production process by specialized adopters.

We start by describing the production sector. A final consumption good is produced by a continuum of competitive firms that use capital, labor and a composite of intermediate goods for production, and whose capital structure consists of equity and defaultable debt because of a tax advantage. Intermediate goods can be used as collateral and are obtained from adopters who facilitate the costly conversion of ideas or blueprints into productive assets. We think of intermediate goods as patents, or intangible capital. Finally, there is a representative agent with Epstein-Zin preferences who consumes and supplies labor.

2.1 Final good producers

The final good in the economy is produced by a continuum of ex ante identical firms $i \in [0, 1]$, that use capital K_{it} and labor L_{it} and a composite of intermediate goods G_{it}. We assume that the final good firms have access to the production technology

$$Y_{it} = (K_{it}^{\alpha}(\Omega_t L_{it})^{1-\alpha})^{1-\xi} G_{it}^{\xi}, \tag{1}$$

where the composite G_t is defined as:

$$G_{it} = [\int_0^{A_t} X_{ijt}^{\frac{1}{\nu}} dj]^{\nu}. \tag{2}$$

X_{ijt} is the quantity of intermediate good $j \in [0, A_t]$, used by firm i. A_t denotes the mass of adopted patents at time t, α is the physical capital share, ξ is the intangible capital share, and $\frac{1}{1-\nu}$ is the elasticity of of substitution between patents with $\nu < 1$.

We introduce uncertainty into the model by means of an exogenous stochastic process Ω_t affecting the level of output. Importantly, Ω_t is assumed to follow a stationary Markov process by specifying that $\Omega_t = e^{a_t}$ and $a_t = \rho a_{t-1} + \epsilon_t$, with $\epsilon_t \sim N(0, \sigma^2)$ and $\rho < 1$. While Ω_t resembles labor augmenting technology, measured productivity is endogenous in our model and depends on the mass of adopted patents. The law of motion for capital is:

$$K_{it+1} = (1 - \delta)K_{it} + \Gamma(\frac{I_{it}}{K_{it}})K_{it}. \tag{3}$$

where δ is the depreciation rate of physical capital and $\Lambda(\cdot)$ the capital adjustment cost function.[1]

2.1.1 Firms' operating profits

Following Gomes, Jermann, and Schmid (2013), we assume that operating profits are hit by an idiosyncratic, mean zero, i.i.d. shock ζ_{it}. The size of the shock to cash flows is $\zeta_{it}\bar{K}_t$, where

[1]We specify $\Lambda(\cdot)$ as in Jermann (1998), $\Lambda\left(\frac{I_{it}}{K_{it}}\right) \equiv \frac{\alpha_1}{\zeta}\left(\frac{I_{it}}{K_{it}}\right)^{\zeta} + \alpha_2$. Here, $\frac{1}{1-\zeta}$ represents the elasticity of the investment rate with respect to Tobin's Q. The parameters α_1 and α_2 are set so that there are no adjustment costs in the deterministic steady state.

$\bar{K}_t$ is the average capital stock. The purpose of this shock is to introduce ex post heterogeneity in firms' performance so that a fraction of firms finds it optimal to default if the shock realization is sufficiently bad. Therefore, these shocks can be potentially large. The iid nature of the shocks facilitates aggregation in a tractable way.

In the following, we denote by Φ the cumulative distribution function of the idiosyncratic shock ζ which is defined over the support $[\underline{\zeta}, \bar{\zeta}]$.

2.1.2 Financing

Firms' owners decide on whether to default or not after all shocks are realized. If no default occurs, the firm chooses its optimal capital structure by issuing new debt, B_{it+1}, and equity to finance its operations. In case of default, the owner walks away with a payoff of zero. The creditors pay bankruptcy costs and take over the firm. Creditors then continue operating the firm and make investment and debt financing decisions. Given our assumptions, all firms are ex-ante identical in each period.

We assume that debt comes in the form of one-period, defaultable bonds with coupon C. The corresponding commitments are

$$((1-\tau)C+1)B_{it}$$

where τ is the corporate tax rate. In accordance with the US tax code, our model thus captures a tax advantage of debt financing through tax deductibility of interest payments. Issuing new debt comes with a cash inflow of

$$Q_{it}B_{it+1},$$

where Q_{it} is the market price of a bond. To capture realistically persistent capital structure dynamics, we also consider financing costs, and assume that all costs associated with adjustments to leverage are captured by a cost function $\psi(B_{it}, B_{it+1})$. Therefore the net cash flow from debt financing activities is given by

$$Q_{it}B_{it+1} - ((1-\tau)C+1)B_{it} - \psi(B_{it}, B_{it+1}).$$

2.1.3 Final good firms' problem

Final goods firms' objective is to maximize equity value, that is, the present value of future dividends. More formally, we have:

$$W_{it} = \max\left\{0, \max_{I_{it}, L_{it}, K_{it+1}, B_{it+1}, X_{ijt}} E_0\left[\sum_{t=0}^{\infty} M_t D_{it}\right]\right\}$$

s.t.

$$D_{it} = (1-\tau)(Y_{it} - I_{it} - \mathcal{W}_t L_{it} - \int_0^{A_t} P_{jt} X_{ijt} dj - \zeta_{it}\bar{K}_t) + Q_{it}B_{it+1} - (1+(1-\tau)C)B_{it} - \psi(B_{it}, B_{it+1})$$

$$K_{it+1} = (1-\delta)K_{it} + \Gamma(\frac{I_{it}}{K_{it}})K_{it}$$

$$Y_{it} = (K_{it}^{\alpha}(\Omega_t L_{it})^{1-\alpha})^{1-\xi} G_{it}^{\xi}$$

Here, M_t is the stochastic discount factor, $\mathcal{W}_t$ is the wage rate, and P_{jt} is the price per unit of patent j. Prices P_{jt} are set by patent producers in the intangible sector, while the stochastic discount factor and the wage rate are determined in general equilibrium and are both taken as given by final good firms. Dividend payments reflect output net of investment in physical capital and the wage bill, as well as purchasing intermediate goods at price P_{jt} and cash flow shocks, all net of corporate taxes. Finally, dividends capture the costs of refinancing in the corporate debt market.

Shareholders will only keep injecting funds into the firm as long as its value is positive. When the latter falls to zero, shareholders declare bankruptcy, as reflected in the maximum operator in shareholders' problem.

2.1.4 Default decision

When firms' equity value reaches zero, shareholders declare bankruptcy and leave with a payoff of zero. In our model, shareholders find it optimal to do so whenever profits are hit by a cash flow shock, which is sufficiently bad, or in other words, whenever $\zeta_{it} \geq \zeta_t^*$, where ζ_t^* is some threshold level. The default decision consists in finding the threshold value ζ_t^*, such that $W(K_{it}, B_{it}, \zeta_t^*, S_t) = 0$.

Here S_t denotes the vector of aggregate states that are taken as exogenous by the firm. Given our assumptions on the nature of the cash flows shock, this threshold can easily be determined. We note that the default decision depends on firm valuations and thus on macroeconomic conditions.

2.1.5 Debt Value

In default, creditors recover a fraction $1 - \Xi$ of the unlevered firm value. Here Ξ represent deadweight losses of default, perhaps representing inefficiencies of the restructuring process, such as the coordination of a diffuse pool of bondholders.

In the case of default, creditors take over the firm, restructure it, and continue operating it. Corporate bonds are held by the representative household and are thus valued using the household equilibrium pricing kernel M_{t+1}. The value of newly issued debt to creditors is thus:

$$Q_{it}B_{it+1} = E_t M_{t,t+1} \left\{ \Phi(\zeta^*_{t+1})(C+1)B_{it+1} + (1-\Xi) \int_{\zeta^*_{t+1}}^{\bar{\zeta}} W(0, K_{it+1}, \zeta_{t+1}, S_{t+1}) d\Phi(\zeta_{t+1}) \right\}$$

The first term inside the brackets is the payment when the firm survives multiplied by the probability of survival. It is equal to the coupon payment plus the principal. The second term is bondholders' payo when the firm defaults, multiplied by the probability of default. Note that given constant returns to scale, and the iid nature of the shocks, after restructuring firms make identical decisions.

The restructured unlevered equity value effectively serves as collateral for bond issuances, in our model. While, given default costs Ξ bonds are not fully secured, increases in expected W effectively raise the collateral value of the bond, and thus facilitate borrowing. By making capital more productive, new patents raise the equity value and increase recoveries. Patents, once in place, thus effectively serve as collateral. This is consistent with the empirical work of Mann (2016), who documents that increasingly, patents are used as collateral to secure debt financing.

2.1.6 Shareholder Optimization

Shareholders choose decisions to maximize firms' equity values. Conditional on survival in the current period, they choose investment, hiring, patent input and financing decisions. The recursive representation of the Lagrangian for the shareholders' problem is given as follows:

$$
\begin{aligned}
L_{it} = {} & (1-\tau)(Y_{it} - I_{it} - W_t L_{it} - \int_0^{A_t} P_{kt} X_{ijt} di - \zeta_{it} \bar{K}_t) \\
& + Q_{it} B_{it+1} - (1 + (1-\tau)C) B_{it} - \psi(B_{it}, B_{it+1}) \\
& + \Lambda_t((1-\delta)K_{it} + \Gamma(\frac{I_{it}}{K_{it}})K_{it} - K_{it+1}) \\
& + E_t M_{t,t+1} \int_{\underline{\zeta}}^{\bar{\zeta}} L_{it+1} d\Phi(\zeta_{t+1})
\end{aligned}
\tag{4}
$$

The last term implies that shareholders take into account the effects of their decisions on future defaults. We detail the derivations and the complete set of first order conditions in the appendix, and discuss those here that are not mostly standard.

The final goods firm i demand for patent j is determined by

$$
P_{jt} \quad = \quad (K_{it}^{\alpha}(\omega_t L_{it})^{1-\alpha})^{1-\xi} \xi \left[\int_0^{A_t} X_{ijt}^{\nu} \, dj \right]^{\frac{\xi}{\nu}-1} X_{ijt}^{\nu-1}, \tag{5}
$$

where it takes the price P_{jt} as given. Importantly, that demand depends on macroeconomic conditions directly through ω_t, and indirectly through K_{it} and L_{it}. A critical implication of the model is that the demand for patents is procyclical. We now show that investment and financing are jointly determined in this setup, implying that the demand for patents also reflects financing conditions.

Indeed, the first order condition for capital, namely

$$
Q'_{K_{it+1},t} B_{it+1} - \Lambda_t + E_t M_{t+1} \int_{\underline{\zeta}}^{\zeta^*_{t+1}} L'_{K_{it+1},t+1} d\Phi(\zeta_{it+1}) = 0,
$$

together with the envelope condition

$$
L'_{K_{it},t} = \frac{\partial L_{it}}{\partial K_{it}} = (1-\tau)\alpha(1-\xi)\frac{Y_{it}}{K_{it}} + \Lambda_{it}((1-\delta) - \Gamma'_{it}(\frac{I_{it}}{K_{it}}) + \Gamma),
$$

shows that the benefits of investment accrue to shareholders only whenever $\zeta_{it+1} < \zeta^*_{t+1}$, that is, whenever default is avoided, as indicated by the truncation of the continuation value. Similarly, shareholders take into account that additional capital increases the value of debt, both by decreasing the default probability and by raising the recovery value in default,which facilitates exploiting the debt tax shield and creates value for shareholders, as the first order condition for debt shows.

Indeed, the optimality condition for new debt issuance

$$Q'_{B_{it+1},t}B_{it+1} + Q_{it+1} - \psi_{B_{it+1},t} + E_t M_{t+1} \int_{\underline{\zeta}}^{\zeta^*_{t+1}} L'_{B_{it+1},t+1} d\Phi(\zeta_{it+1}) = 0,$$

together with the envelope condition

$$L'_{B_{it},t} = \frac{\partial L_{it}}{\partial B_{it}} = -((1-\tau)C + 1) - \psi'_{B_{it}},$$

shows that shareholders benefit from tax savings as long as they can avoid default. However, at the optimum, these benefits are offset by the marginal increase in default probability through an additional bond, as well as the associated transaction costs. Indeed, worth noticing is that equity holders rationally take account of the impact of their choices on the cost of debt, as reflected in the term $Q'_{B_{it+1},t}$.

Taken together, the optimality conditions show that financing, investment and patent input are inherently linked in our model. While, in the spirit of a trade-off model of capital structure, firms issue debt exclusively to exploit the tax shield, the availability of such value creation depends on capital and patents. Patents make capital more productive and therefore increase the recovery rates in default, and thus facilitate borrowing and exploitation of the tax shield. In other words, firms can borrow against patents, so that they serve as collateral.

2.2 Intermediate good producers

Patents are produced in the intermediate goods sector. Monopolistic competition prevails in the market for intermediate goods. Given the demand schedules set by the final goods firm, a contiunuum of monopolists $j \in [0,1]$ producing the patents set the prices P_{jt} in order to maximize their profits Π_{jt}. Patent producers transform one unit of the final good into one unit of their patented good. This fixes the marginal cost of producing one patent at unity.

Formally, monopolists solve the following static profit maximization problem each period

$$\Pi_{jt} \equiv \max_{P_{jt}} P_{jt} \cdot X_{ijt}(P_{jt}) - X_{ijt}(P_{jt}). \tag{6}$$

The value V_{jt} of owning exclusive rights to produce patent j is equal to the present discounted value of the current and future monopoly profits, so that

$$V_{jt} = \Pi_{jt} + (1-\phi)E_t[M_{t+1}V_{jt+1}], \tag{7}$$

where ϕ is the probability that a patent becomes obsolete. This asset price is important in our model, as it provides the payoff to creating new patents through adoption as we describe next. This highlights the importance of monopoly power, as the associated profits provide the rents to innovation.

In the symmetric equilibrium, absent cross-sectional heterogeneity, we have

$$P_{jt} = P_t = \frac{1}{\nu}$$

$$X_{ijt} = X_t$$

$$\Pi_{jt} = \Pi_t$$

. That is, each patent producer charges a markup $\frac{1}{\nu} > 1$ over unit marginal cost. Note that X_t is determined by the final good firms' optimality conditions.

Patent values reflect monopoly profits, which in turn reflect final good firms' demands for patents. This suggests that patent valuations are procyclical, which implies that the incentives for adoption and creation of new patents is likely procyclical as well.

2.3 Adoption Sector

Technological innovations arrive exogenously to the economy. They take the form of new ideas, or blueprints. Upon arrival, these blueprints are not yet ready to be used for production. To be used in production, they first need to be adopted, which is costly. Increasing the likelihood that a blueprint is successfully adopted and becomes usable in the production process requires resources. Critically, in our model, adoption not only makes blueprints usable in the production process, but it also creates collateral value that firms can borrow against. The value of collateral in the economy is thus closely linked to the adoption of new blueprints.

We assume that the average stock of blueprints Z_t evolves according to the law of motion:

$$Z_{t+1} = (\bar{\chi}\chi_t^{\xi^*} + \phi)Z_t$$

where ϕ is the probability of survival of a technology. The process χ_t determines the stochastic growth rate of the stock of technological innovations, which we assume to follow the autoregressive process:

$$\log \chi_t = \rho \log \chi_{t-1} + \eta_t$$

The effect of the shock on the stock of technologies is measured by the slope coefficient $\bar{\chi}$ and the elasticity ξ^*. The process of the stock of technologies captures the idea of spillovers.

Critically, η_t effectively serves as a shock to growth potential. A positive innovation to Z_t implies that there are abundant blueprints available in the economy, which can improve productivity in the economy upon successful adoption. However, adoption is stochastic and costly, as we describe next. We will refer to η_t as innovation or idea shocks, in the following. The notion of shocks to growth potential shares similarities with news shocks, broadly entertained in the macroeconomic literature, such as Beaudry and Portier (2006), with the difference that our innovation shocks only improve productivity upon adoption, a feature similar to embodied investment-specific technology shocks considered, for example, in Kogan and Papanikolaou (2014). An alternative interpretation of positive shocks to growth potential lies in innovations to sentiments.

New blueprints are not yet ready to be used in the production process. They first need to be adopted at a cost. At each point in time a continuum of unexploited technologies is available to be adopted. Through a competitive process, firms that specialize in adoption try to make these technologies usable. These firms, which are owned by households, spend resources attempting to adopt the new goods, which they can then sell on the open market. They succeed with an endogenously determined probability. Once a technology is usable, any producer can use it in production immediately.

Let A_t be the stock of already adopted technologies, and $\lambda_t(H_t)$ be the success probability of adopting a new technology after investing the amount of resources H_t. We specify $\lambda_t(H_t)$ to be of the form:

$$\lambda_t(H_t) = \Lambda H_t^{\kappa}$$

The stock A_t follows the law of motion:

$$A_{t+1} = \lambda(H_t)\phi(Z_t - A_t) + \phi A_t$$

Optimal adoption expenditures H_t satisfy the following Bellman equation:

$$J_t = \max_{H_t} \{-H_t + \phi E_t \left[M_{t,t+1}(\lambda(H_t)V_{t+1} + (1 - \lambda(H_t))J_{t+1})\right]\}$$

The Bellman equation captures the notion that upon successful adoption, which happens with probability $\Lambda(H_t)$ when adopters spend H_t, adopters can sell it to the intermediate goods sector at the fair value V_t, while with probability $1 - \lambda(H_t)$ the option value J_{t+1} of adoption in the future remains. Given procyclical payoffs to adoption, this suggests that adoption expenditures will likely be procyclical as well.

2.4 Household

The household sector is standard. The representative household has Epstein-Zin preferences defined over consumption:

$$U_t = \left\{(1 - \beta)C_t^{\theta} + \beta(E_t[U_{t+1}^{1-\gamma}])^{\frac{\theta}{1-\gamma}}\right\}^{\frac{1}{\theta}}, \tag{8}$$

where γ is the coefficient of relative risk aversion and $\psi \equiv \frac{1}{1-\theta}$ is the elasticity of intertemporal substitution. When $\psi \neq \frac{1}{\gamma}$, the agent cares about news regarding long-run growth prospects. We will assume that $\psi > \frac{1}{\gamma}$ so that the agent has a preference for early resolution of uncertainty and dislikes uncertainty about long-run growth rates.

The household maximizes utility by participating in financial markets and by supplying labor, subject to the budget constraint

$$C_t + T_t + S_{t+1}Q_{t,total} + B_{t+1} + B_{g,t+1} = S_t\left(\int_{\zeta_t^*}^{\bar{\zeta}} (Q_{final,t} + D_t(z_t))d\Phi(\zeta_t) + Q_{innov,t} + D_{innov,t}\right) + \mathcal{W}_t L_t + R_{c,t}B_t + R_{f,t}B_{g,t}, \tag{9}$$

where T_t is a lump-sum transfer from the government to the household; $S_t \in [0 \quad 1]$ represents the percentage ownership of capital; $Q_{t,total}$ is the ex-dividends value of capital including both tangible and intangible capital; D_t is the final firm corporate payout; $D_{innov,t}$ is the innovation sector payout; $\mathcal{W}_t$ is the wage; $L_t \in [0 \quad 1]$ is the hours worked. B_t are corporate bonds and $B_{g,t}$ are government bonds. Since the agent has no disutility for labor, she will supply her entire endowment, which we normalized to unity, so that $L_t \equiv 1$.

The stochastic discount factor takes the following standard form:

$$M_{t,t+1} = \delta\left(\frac{C_{t+1}}{C_t}\right)^{-\frac{1}{\psi}}\left(\frac{U_{t+1}}{E_t[U_{t+1}^{1-\gamma}]^{\frac{1}{1-\gamma}}}\right)^{\frac{1}{\psi}-\gamma}$$

where the second term, involving continuation utilities, captures preferences concerning uncertainty about long-run growth prospects.

2.5 Resource Constraint

Absent ex ante cross-sectional heterogeneity, we focus on a symmetric equilibrium in which all firms are identical (possibly after restructuring). Final output is used for consumption, investment in physical capital, factor input used in the production of intermediate goods, adoption, resources lost in restructuring and debt adjustment costs:

$$Y_t = C_t + I_t + A_t X_t + H_t(Z_t - A_t) + \Xi \int_{z_t^*}^{\bar{z}} W(K_t, 0, \zeta_t, S_t) d\Phi(\zeta_t) + \psi(B_t, B_{t+1})$$

where $Y_t = \int_0^1 y_{it} di$, $I_t = \int_0^1 i_{it} di$ and $H_t = \int_0^1 H_{it} di$. Note that from a national income accounting perspective, we have that $GDP_t = Y_t - A_t X_t - \Xi \int_{\zeta_t^*}^{\bar{\zeta}} W(K_t, 0, \zeta_t, S_t) d\Phi(\zeta_t) - \psi(B_t, B_{t+1})$, so that we obtain

$$GDP_t = C_t + I_t + H_t(Z_t - A_t).$$

2.6 The Stock Market and Returns

Given the multi-sector production structure, we can consider various claims and returns, that we define in the following. To begin with, we define the aggregate stock market as a claim to the net payout of all production sectors. In the symmetric equilibrium, the aggregate dividend then becomes

$$\mathcal{D}_t = D_t + \Pi_t A_t - H_t(Z_t - A_t)$$

Defining the stock market value to be the discounted sum of future aggregate dividends and exploiting the optimality conditions, this value can be rewritten as

$$\mathcal{Q}_t = W_t + (V_t - \Pi_t) A_t + (J_t + H_t)(Z_t - A_t) + E_t[\sum_{r=t+1}^{\infty} M_{t,r} J_r (Z_r - \phi Z_{r-1})]. \tag{10}$$

In our model with stochastic arrival of new blueprints, unlike other models, firms have the rights to the profit flows from selling current and future adopted technologies. Thus, the stock market value is given by the present discounted value of these profits in addition to the value of installed capital, similar to Comin, Gertler and Santacreu (2009).

The first term captures the fact that the market values the capital stock installed in firms. Note that in our model, W_t also reflects value creation through the debt tax shield as well as default probabilities. The second term reflects the market value of patents currently used by productive firms. The third term corresponds to the market value of blueprints available for adoption, but not yet successfully transformed to usable patents. The final term captures the market value of the blueprints that will arrive in the future, that is, the option value of future growth options. Since adopters have the unique ability to transform blueprints into patents, the associated rents also have a value which is priced in by the market.

We can define returns on the aggregate stock market, as well as on the individual components. In the following, we will refer to return on final equity as follows:

$$R_{e,t} = \frac{\int_{\zeta_t^*}^{\bar{\zeta}} W_{,t}(\zeta_t) d\Phi(\zeta_t)}{W_{t-1}(\zeta_t) - D_{t-1}(\zeta_t)}$$

Similarly, we define $Q_{final,t} = W_{t-1}(\zeta_t) - D_{t-1}(\zeta_t)$ is the ex-dividend value of the final firm, which is identical across all firms. Corporate bond returns can be defined as follows:

$$R_{c,t} = \frac{\Phi(\zeta_t^*)(C+1)B_t + (1-\Xi)\int_{\zeta_t^*}^{\bar{\zeta}} W(0,\zeta_t) d\Phi(\zeta_t)}{Q_{t-1}B_t}$$

Finally, it is convenient to define the returns on adoption as follows:

$$R_{a,t+1} = \lambda'(H_t)\phi(V_{t+1} - J_{t+1}).$$

Bond Excess Premium The pricing of corporate debt reflects expected losses in default. With realistic default rates, these losses give rise to a non-trivial credit spreads. However, in our risk-sensitive setting, the pricing of corporate bonds also captures the timing of default. That is, credit spreads also contain a risk premium that compensates agents for the systematic risk of incurring losses in downturns, when marginal utility is highest. With realistically countercyclical default rates, this risk premium can be substantial, as emphasized by Chen, Collin Dufresne, and Goldstein (2010). Following the terminology introduced by Gilchrist and Zakrajsek (2010) and adopted by the empirical literature, we refer to that risk premium as the *bond excess premium*.

The bond excess premium is most conveniently computed using the recovery rate in default. The recovery rate is given by

$$R_{rec,t+1}(\zeta_{t+1}) = \frac{(1-\Xi)W(K_{t+1}, 0, \zeta_{t+1}, S_{t+1})}{Q_t B_{t+1}}.$$

Accordingly, the bond excess premium can be determined as

$$\text{bond excess premium} = Cov_t(M_{t+1}, \int_{\zeta^*_{t+1}}^{\bar{\zeta}} (R_{f,t} - R_{rec,t+1}(\zeta_{t+1}))d\Phi(\zeta_{t+1})) \tag{11}$$

. Indeed, we can decompose (log) credit spreads approximately as

$$\log cs_t \approx \frac{E_t\left[\int_{\zeta^*_{t+1}}^{\bar{\zeta}} (R_{f,t} - R_{rec,t+1}(z_{t+1}))d\Phi(\zeta_{t+1})\right]}{R_{f,t}} + Cov_t(M_{t+1}, \int_{\zeta^*_{t+1}}^{\bar{\zeta}} (R_{f,t} - R_{rec,t+1}(\zeta_{t+1}))d\Phi(\zeta_{t+1}))$$

The first term captures expected losses in default and the second term is a risk premium. The appendix collects further details about the decomposition.

3 Quantitative Analysis

We now present quantative evidence based on model simulations. We start by discussing our parameter choices and then turn to evaluating implications for asset prices and credit cycles. We then provide an interpretation of our results in the context of the private equity industry.

3.1 Calibration

We present the parameter choices for our benchmark calibration in Table 1 . The model behavior is robust to modest variations around this benchmark. We present a quarterly calibration and solve the model using higher order perturbation methods.

Most of our parameter choices are quite standard. We choose values for the preference parameters following the long-run risk literature, involving an intertemporal elasticity of substitution, ψ larger than unity, so that agents are averse to movements in expected growth prospects.

Regarding the production parameters, α is set to 0.35 to match the average capital share and the quarterly depreciation rate of capital δ_k is set to 0.02, a standard choice in the macroeconomic literature. Our choice of the investment adjustment costs elasticity ζ follows Croce (2014), while the markup is consistent with the balanced growth restriction according to Kung and Schmid (2015), and the patent share ξ corresponds to the estimate from Comin and Gertler (2006). The latter reference is also the basis for our choices of the parameterization of the innovation and adoption sectors, that is, the patent survival rate, the adoption elasticity and technology innovation elasticity. More specifically, the patent survival rate coincides with the depreciation rate imputed by the BLS in its calculation of the R&D stock. That R&D stock is meant to provide a measure of the economic benefits of R&D that spillover from the innovating firm to other firms, much as adopted patents in our economy do. The adoption scale parameter determines how quickly new blueprints are available for productive use. Our parameter choice yields an average adoption time of five years, within, but at the lower end, of the bounds estimated by Comin and Gertler (2006).

We choose bankruptcy costs Ξ to target a mean recovery rate in default of 40%, which is consistent with the estimates in Chen (2010). The corporate tax rate is set to yield an aggregate mean book leverage ratio as reported in Gourio (2013). Similarly, the debt adjustment cost parameter is chosen to match the latter's standard deviation. The volatility of idiosyncratic shocks implies a quarterly average default rate of 0.25%, which matches Moody's average annual default rate of about 1% per year.

The specification of the productivity and innovation shocks jointly determine the dynamics of measured TFP in our model. In line with Comin and Gertler (2006), we choose the parameters to match not only the standard business cycle properties of TFP, but also the medium term dynamics, extracted as movements at frequencies of 2 to 50 years using a bandpass filter. These movements reflect the dynamics of innovation that occur at frequencies different from the standard business cycle. As argued in Kung and Schmid (2015), such cycles are akin to long-run risks in asset markets as proposed in Bansal and Yaron (2004). Specifically, we choose the parameters of the productivity process to match the business cycle properties of measured TFP, and those of the innovation shocks to generate realistic medium term dynamics. The choices are also broadly consistent with the parameterization in Comin, Gertler and Santacreu (2009).

Returns Our productivity-driven model naturally generates rather low volatility in returns. Indeed, Ai, Croce and Li (2010) report that empirically the productivity-driven fraction of return volatility is just around 6%. Similarly, given low adjustment costs and persistent growth shocks, our model generates rather highly autocorrelated returns in certain sectors [2]. In order to better compare the results of the model to the data, and to account for sources of return volatility the model is silent on, we also consider the following excess returns on final good equity and the market portfolio, respectively,

$$R^{ex}_{e,t} = R_{e,t} - R^{f}_{t-1,t} + \sigma_{d,e}\epsilon_t$$

$$R^{ex}_{market,t} = R_{market,t} - R^{f}_{t-1,t} + \sigma_{d,market}\epsilon_t$$

where $\epsilon_t \sim N(0,1)$. The cash-flow shock ϵ_t, is not priced and hence does not alter the equity premium and only affects the volatility of the excess returns. We set $\sigma_{d,e}$ and $\sigma_{d,market}$ so that the annualized volatility increases by 6.5%, following with Croce (2012) and Bansal and Yaron (2004). With this specification, the autocorrelations of all returns are in the empirical range documented in Croce (2012).

3.2 Results

Table 2 gives an overview of the overall fit of the calibrated model regarding basic macroeconomic, asset pricing and credit market moments. As targeted by our calibration, and reported in panel A, the model is consistent with basic macroeconomic data such as aggregate risk and consumption risk. Given moderate investment adjustment costs, the model generates relatively volatile investment growth rates. Given persistent innovation shocks, the autocorrelation of consumption growth is on the higher end, but within the empirical confidence band reported in Croce (2012). Perhaps more importantly, the average level and dynamics of aggregate (book) leverage are consistent with their empirical counterparts. While book leverage is procyclical, in that firms issue debt in expansions when default risk is relatively low, market leverage is mildly countercyclical, as equity values fall relatively more than debt prices in downturns.

Panel B report basic asset price moments, focusing on the returns on levered final good firm equity, the returns to adoption, the overall market portfolio, as well as the risk free rate. The model does a reasonable job quantitatively capturing basic patterns in asset markets. As a first

[2] We thank Dimitris Papanikolaou for pointing this out to us.

pass, the model generates a non-trivial equity premium, with a sizeable volatility. Such results are often hard to achieve in general equilibrium models with production, which are well known to imply excessively low volatility of the returns to capital. The results here reflect both the presence of persistent shocks to innovation, resulting in long run risks that are priced with recursive preferences, similar to Kung and Schmid (2015), as well as our endogenous modeling of leverage. While long run risks raise the market price of risk, accounting for endogenous leverage raises the volatility of returns. While we focus on unconditional moments here, the dynamics of leverage also give rise to realistic patterns in conditional expected returns that we discuss later. Although lower, the model still generates significant returns to adoption. We will later interpret those returns in the context of venture capital (VC) funds, but do not attempt to give a quantitatively realistic account of the associated returns. Finally, owing to a high intertemporal elasticity of substitution of the representative household, the model features a low and stable risk free rate.

Turning to panel C, we find that the model also produces a sizeable credit spread not too far below the approximately one percent annual BBB-AAA spread on corporate bonds. Moreover, the credit spread is quite volatile and realistically countercyclical. In our model with risk averse bond investors, credit spreads reflect both average expected losses in default and a risk premium compensating investors for losses in downturns. Since the model is calibrated to match average default probabilities and recovery rates, the implied credit risk premium, the bond excess premium in other words, is sizeable.

To get a sense of the dynamics of the aggregate risks underlying risk premia in the model, figure 1 illustrates the effects of standard neutral and innovation shocks on quantities, by means of impulse responses to one standard deviation positive technology and idea shocks. It is relevant to note that the nature of these shocks is sufficiently different that they often drive quantities in opposite directions. Moreover, innovations to future growth potential come with slow buildups in quantities, such as future consumption and investment growth, reflecting the slow adoption of technological innovations.

These macroeconomic dynamics are reflected in asset valuations and credit markets, as figure 2 shows. Importantly, and perhaps unsurprisingly, the responses to a neutral technology shock all go in the same, expected direction. The shock increases the value of the aggregate stock market as well as bond valuations, as it decreases default probabilities, in spite of elevated leverage. This is because recovery and collateral values rise, and it is beneficial for firms to exploit the associated tax benefits. This is quite in contrast to the responses to an innovation shock, depicted in the right panel. The aggregate stock market appreciates, if only slowly, in anticipation of future rents from the adoption of blueprints. This is in contrast to the values of final goods firms, which fall on impact, a manifestation of displacement by new technologies. This is reflected in the fall of bond prices on impact, as default probabilities rise, only to slowly recover as new blueprints are adopted and transformed into collateral value. Aggregate leverage follows a similar pattern. In this sense, stock and corporate bond prices may temporarily diverge after an innovation to growth potential, so that debt, or equity for that matter, may be relatively cheap.

These cycles are reflected in the pricing of risk, as figures 3 and 4 show. Figure 3 shows the response of the stochastic discount factor with respect to *negative* neutral technology and idea shocks, respectively. The rise in the stochastic discount factor in both cases implies that both shocks carry a positive price of risk. This is despite the opposite movements in consumption growth, and therefore mostly reflects the dynamics of continuation utilities. Indeed, in our calibration with a high IES, a persistent negative idea shock is bad news for future growth, in spite of the short-run rise in consumption growth.

More importantly, the conditional volatility of the stochastic discount factor exhibits relevant dynamics and different responses to the two sources of risk. Figure 4 shows that, perhaps not surprisingly, the conditional volatility of the stochastic discount factor falls after a positive technology shock, in spite of a rise of short-run consumption risk. Intriguingly, the opposite happens after a positive innovation shock. The conditional volatility of consumption growth falls, but nevertheless, the conditonal volatility of the stochastic discount factor rises. This is because the arrival of a good idea leads to higher uncertainty about future growth, reflecting uncertainty about the speed of adoption.

Our model thus exhibits endogenous time variation in the market price of risk, linked to the arrival of new technologies, and thus along the adoption-driven credit cycle. This is despite the fact that the model is driven by two homoskedastic sources of risk. Table 3 shows that a variable that we find indicative of the adoption-collateral cycle in the model, namely, the ratio of ideas to capital,

$\frac{Z_t}{K_t}$, what we will refer to as the IC ratio henceforth, has predictive power for asset returns. A high IC ratio, consistent with the dynamics of the stochastic discount factor, predicts high returns on stocks, as well as high excess returns on corporate bonds, as Table 3 shows, although the latter is statistically weaker.

Table 4 gives a sense of the underlying model mechanisms by considering two variants of the baseline calibration. The first features a higher tax rate resulting in higher leverage. The second features instantaneous technology adoption in that new blueprints are immediately available for productive use at no cost of adoption. Raising the tax benefits of leverage results in substantially steeper predictive coefficients. This is because final good firms are eager to increase leverage in response to positive shocks in order to exploit the tax benefits of debt financing, thereby quickly increasing their exposure to aggregate risks. At the same time, leverage becomes more cyclical. On the other hand, allowing for instantaneous diffusion, thereby minimizing adoption lags, substantially weakens return predictability. While firms still increase their exposure to aggregate risks by levering up in expansions, innovation shocks lead to immediate productivity gains and reduce uncertainty about future successful adoptions reflected in continuation utilities. Instantaneous diffusion thus reduces the conditional volatility of the stochastic discount factor, and thus movements in the market price of risk, thereby reducing return predictability.

In our model, leverage and the IC ratio thus emerge as state variables capturing the stage of the credit cycle induced by the slow transformationo of new ideas into collateral. Figures 5, 6, 7, and 8, illustrate epected excess returns and the volatilities of the stochastic discount factor, conditional on the stage of the credit cycle, as captured by these state variables. Figure 5 shows that expected excess returns on productive firms tend to fall with the IC ratio. This is in contrast to the expected excess return on the market portfolio, and on adoption. These latter, *unlevered* expected excess returns rise with the increase in the conditional volatility of the stochastic discount factor that good news to growth potential bring about, as reflected in IC ratios. Indeed, as the lower right panel shows, leverage falls with the IC ratio, reflecting a relative shortage of collateral. Figure 6 shows that the conditional volatility of the stochastic discount factor increases with the IC ratio. On the other hand, figure 7 shows that once new ideas are adopted and can be used as collateral, the expected excess returns on productive firms rise. This reflects the additional risk exposure through leverage, as the market price of risk concurrently falls, as documented in 8. In line with that reduction in the market price of risk, the expected returns on unlevered innovation tend to fall.

In the model, unlevered adoption returns are especially sensitive to equilibrium movements in volatility. Table 5 presents evidence to this effect. Movements in the conditional volatility of the stochastic discount factor, that is the market price of risk, predict adoption return significantly positively going forward. On the other hand, the slope coefficients in the predictive regressions for final firms are negative, albeit not strongly significantly different from zero. This becomes more intuitive in light of the lowest panel showing that volatility also predicts higher credit spreads in the future. Levered firms endogenously react to the increasing costs of debt financing by decreasing their leverage, thereby reducing their exposure to volatility.

Perhaps unsurprisingly, movements in credit spreads in response to fluctuations in discount rates are reflected in credit market activity, as Table 6 documents. When the market price of risk increases, not only do credit spreads rise, but also the excess bond premium, that is, the compensation for systematic risk in default pricing. At the same time, when issuing debt becomes more expensive, corporate leverage falls, both in market and book terms.

3.3 Application: VC and Buyout

Our model is agnostic about the exact nature of the adopters, and the final good firms. We now provide an interpretation of some of our model results that is clearly no more than suggestive, but which we find natural. This interpretation is in the context of the private equity industry, and especially VC and buyout funds. Capital structure decisions are at the heart of private equity funds' strategies, so that they are potentially informative about the nature and the stage of the credit cycle.

In this regard, we can view adopters as venture capitalists that fund the risky transformation of promising ideas into marketable products. Most of the funding for early ventures comes in the form of equity injections, consistent with our model and the lack of collateral to facilitate debt financing for that purpose. Selling successfully adopted blueprints as new patents to intermediate goods can be thought of as a successful exit of a VC through an IPO. Our productive firms, on the other hand, take advantage of access to collateral to fund the use of new technologies with debt, which perhaps broadly resembles buyout funds using leverage to increase the productivity of their portfolio companies and to benefit from the tax shield. Similarly, buyout firms tend to invest more likely into mature firms with ample collateral and stable cash flows, value firms in other words, rather than the growth firms that our intermediate goods producers and adopters look alike.

Clearly, this mapping between sectors in our model and asset classes in the private equity industry is based on what we think is a natural association between leverage and risk profiles only, and completely abstracts from any considerations regarding organizational form. In particular, there is no notion of public versus private equity in our model, or for that matter, any consideration regarding the costs and benefits of being private versus public that our model could speak to.

That said, we argue that a number of stylized patterns about flows and returns to VC and buyout funds in recent years emerge quite naturally from our model. For example, flows into venture capital occur when the IC ratio and thus the market price of risk are high, so that (unlevered) expected returns to adoption are high. Incidentally, the great VC wave occurred during the tech boom in the late 90s, at a time when volatility, as measured by the VIX rose to elevated levels and implied measures of risk premia in the corporate bond market (such as the Gilchrist-Zakrajsek excess bond risk premium) were rising. It is therefore tempting, and we think natural, to interpret the tech boom as an episode when an innovation shock increased growth potential, or perhaps sentiment, but uncertainty about future successful adoptions increased the market price of risk, leading to high expected returns to adoption. Indeed, empirically, Peters (2016) documents that VC returns at the aggregate, fund, and portfolio company level load positively on innovations to volatility. A reminiscent pattern emerges in our model in that adoption returns, in contrast to final firm returns, are significantly positively predicted by volatility, as shown in table 5 .

Buyout waves, in turn, do not occur simultaneously but at a later stage of the credit cycle, when there is ample collateral and spreads on defaultable debt are relatively low. Importantly, the model predicts that in such episodes the market price of risk is relatively low, so that high expected returns on buyout funds mostly reflect leverage and expected productivity gains. Incidentally, the large buyout waves preceeding the financial crisis of 2008 occurred in the aftermath of the tech boom, when the GZ bond excess premium and the VIX had fallen back to minimal levels. The ensuing credit boom came with rising leverage, and thus higher exposure to aggregate risk when risk prices were low. In our model, this credit boom reflects abundant supply of collateral in the aftermath of adoption. These dynamics are consistent with the empirical findings of Axelson, Jenkinson, Stromberg and Weisbach (2013), who examine the importance of the relative pricing of credit and equity instruments in shaping buyout activity and show that buyout activity occurs when debt is relatively cheap, and of Haddad, Loualiche, and Plosser (2017), who document that buyout waves coincide with low aggregate discount rates. More specifically, table 6 shows that in the model, the pricing and magnitude of debt financing is significantly related to aggregate discount rates, in a direction consistent with the evidence in Haddad, Loualiche, and Plosser (2017).

Again, it is tempting, and natural through the lens of our model, to view the VC boom and the buyout waves as linked as distinct manifestations of different stages of the credit cycle. This notion resonates more broadly with the observation (see e.g. Cao and L'Huillier (2016)) that most debt-fueled major recessions in developed countries, such as the recent great recession and the great depression in the US, as well as the long Japanese slump of the 1990s, were preceded by periods of great technological innovation.

4 Empirical Applications and Evidence

As a key indicator of the credit cycle, the IC ratio should be informative about future movements and activity in credit markets. These movements should reflect the availability of collateral in the model. As the latter is driven by the slow transformation and diffusion of new blueprints into productive technologies, we would expect any predictive power to be strongest over the medium term. Given an average adoption lag of about 5 years in our calibration, we now investigate the predictive power of the IC ratio for credit market activity over these medium term horizons and distill the findings into empirical predictions. We then use an empirical proxy for the IC ratio, based on the number of patent applications as a stand-in for blueprints, as well as the aggregate capital stock as a measure of collateral, to validate the predictions. We use aggregate credit market data, measures of credit spreads and returns, as well as measures that are suggestive of our interpretation of the model in the context of the private equity industry.

4.1 Empirical Predictions

The essence of the model is that after a slow adoption process, innovation booms lead to collateral and lending booms over medium horizons. Such a lending boom reflects two equilibrium forces that are tied to the availability of collateral in the model, namely a *quantity* channel, and a *risk premium* channel. The quantity channel simply reflects that losses given default fall when there is ample collateral. Since losses given default constitute a component of the credit spread, as discussed earlier, credit spreads should fall after an innovation boom, facilitating debt issuance. On the other hand, as emphasized for example in Chen, Collin Dufresne, and Goldstein (2010), Chen (2010) and Bhamra, Kuehn, and Strebulaev (2010), corporate bond prices also contain significant compensation for systematic default risk, which reflects market prices of risk. As discussed previously, a critical mechanism in our model is that the equilibrium market price of risk falls with the availability of collateral. Therefore, the risk channel predicts that not only the expected loss component in credit spreads should fall after a technology boom, but also the credit risk premium. Following the terminology introduced in the empirical literature by Gilchrist and Zakrajsek (2010), we refer to that risk premium as the bond excess premium in the following. Clearly, with both components of credit spreads falling, we should expect corporate leverage to rise with the adoption of collateral after an inovation boom.

We now distill that intuition into empirical predictions through model simulations. To that end, we predict credit spreads, bond excess premia, as well as market and book leverage over medium term horizons using Z_t/K_t as the model equivalent of the IC ratio. More specifically, we run the following forecasting regression

$$\frac{1}{n}\sum_{i=0}^{n-1} CreditMeasures_{t+1+i} \quad = \quad \mu + InnovationMeasures_t + \epsilon_{a,t+1}$$

In line with an average adoption lag of about five years, we focus on horizons from five to eight years. Table 7 presents the predictions. Consistent with the intuition developed through the lens of the model, we find evidence for both a quantity channel, in that the IC ratio predicts credit spreads to fall over longer horizons, and of a risk premium channel, in that the bond excess premium falls as well, reflected in increases in both market and book leverage. We note that, comparing these predictions with the results in table 3 that in contrast to medium term bond excess premia, short term stock returns actually increase after an investment boom, consistent with the idea of an adoption lag.

4.2 Empirical Evidence

To give more empirical content to our model of an innovation driven credit cycle, we now validate some of the predictions presented above empirically. We start by discussing the data.

4.2.1 Data

Our main empirical innovation measure is based on patent data from U.S. Patent Trademark Office. Annual data series are available from 1840 to 2013. Total patent applications and total issued patents are accumulated from in-force and issued patents by NBER sub-category in each year. See Marco, Alan C. and Carley, Michael and Jackson, Steven and Myers, Amanda F., The USPTO Historical Patent Data Files: Two Centuries of Innovation (June 1, 2015) for further details.

To obtain a measure of blueprints relative to collateral, we scale the patent measure by the private capital stock K_t. Capital stock data are from the NIPA table 5.10. In our sample, the annual data series are from 1951 to 2013. Only fixed assets (structures, equipment, and intellectual property products) are considerd. Inventories are not included in the measurement.

Our measures for credit spreads and bond excess premia come from Gilchrist and Zakrajsek (2010). They introduce a corporate bond credit spread with a high information content for economic activity that is built from the bottom up, using secondary market prices of senior unsecured bonds issued by a large representative sample of U.S. non-financial firms. To avoid duration mismatch issues, which can contaminate the information content of credit-risk indicators, yield spreads for each underlying corporate security are derived from a synthetic risk-free security that exactly mimics the cash flows of that bond. Furthermore, an excess bond premium is extracted from the GZ spread by first using a linear regression to remove expected default risk of individual firms from the underlying credit spreads. This procedure empirically isolates a credit risk premium distinct from expected losses in credit spreads. As an alternative measure of risk premia in the corporate bond market, we consider returns on a portfolio of long-term corporate bonds, as available from Ibbotson.

We construct aggregate measures of leverage by aggregating leverage across COMPUSTAT firms. In particular, book debt (BD) is the sum of debt in current liabilities (DLCQ) and long-term debt (DLTTQ). Book value of equity (BE) is common ordinary equity (CEQQ).Market value of equity (ME) is the quarter-end price (PRCCQ) times shares outstanding (CSHOQ). Market leverage is BD divided by the sum of BD and ME. Book leverage is BD divided by BE. Those company-level series are then aggregated to two aggregate series by value-weighting. Finally, following Bai (2016), we use credit growth, constructed as $\frac{\text{Debt Issuance}}{\text{Business GDP}}$ as an alternative indicator of credit market activity.

Regarding data on buyout activity, we rely on the data provided in Haddad, Loualiche, and Plosser (2017), on their websites. That sample of U.S. buyouts comes from Thomson Reuters SDC M&A data. Public-to-private buyout transactions are identified as completed deals for public targets that are described as a leveraged buyout or management buyout. Because the SDC descriptor misses some notable buyout deals, additional transactions are screened for by including firms purchased by private financial acquirers where the acquisition is made for investment purposes. Each of these transactions is checked to verify that the purchaser is indeed a private equity firm. From that data, they obtain two aggregate measures of buyout activity from 1982, Q4 to 2011, Q4. We use buyout value, obtained as the logarithm of total target assets.

As indicators of risk and returns in the private equity industry, we use aggregate returns in the VC as well as the buyout ('buyout and growth equity') industry provided by Cambridge Associates. Cambridge Associates provides quarterly series of pooled internal rates of returns (IRRs) from a large set of VC and buyout funds. Clearly, given that these returns are effectively IRRs and not realized returns, and that the set of funds is large but likely not exhaustive, these returns are at most suggestive. Similarly, it is well understood that these return indices are likely subject to asynchronous prices resulting from the fact that PE funds infrequently update (mark to market) the value of their portfolio holdings. Nevertheless, we find it informative to include them in our analysis.

The appendix contains further details about our empirical procedure and the data used.

4.2.2 Evidence

Based on our empirical proxies, table 8 reports regressions evidence for credit market activity along the lines of the model predictions , while table 9 examines various measures of credit pricing implicit in credit spreads and 10 presents empirical evidence regarding returns across various relevant asset classes. The samples in the respective regressions differ based on data availability. In the samples relevant for our credit variables, namely from the 1980s onwards, the ratio of patent applications to the real private capital stock (deflated by the CPI) is non-stationary, and exhibits a clear trend. To obtain stationary versions, more readily comparable to the model variable, we scale patent applications by the nominal capital stock (to obtain the series ZK_{nom}), we remove a linear trend from patent applications deflated by the real capital stock (to obtain the series ZK_{lin}), and we extract cyclical components by means of a one-sided HP-filter (as in Stock and Watson (1999)) to obtain the series ZK_{HP}, respectively. We do the latter to alleviate concerns regarding look-ahead biases.

Table 8 shows that our empirical proxies for the IC ratio based on the number of patent applications predict market and book leverage positively over the medium run, and often statistically significantly so. Future credit growth is similarly positively related to innovation measures, and often statistically significantly. We note that the HP-filtered IC ratio predicts slowdowns in future credit growth, but the point estimates are not statistically significant. Interestingly, and in the spirit of our interpration of the model in the context of the buyout industry, a similar pattern arises with respect to buyout valuations over the medium term. These results are statistically somewhat weaker but still informative in our view and thus we view them as broadly supportive of our interpretation.

Movements in credit market activity should line up with the pricing of debt instruments. Table 9 provides evidence supporting a link between adoption related fluctuations in debt financing and credit spreads. Indeed, it shows that our empirical proxies for the IC ratio predict credit spreads significantly negatively across many medium term horizons, consistent with the model predictions. A rise in blueprints thus tends to come with a fall in the future pricing of corporate debt. The results for the bond excess premium are similarly negative. An innovation boom thus not only comes with lower expected losses going forward, but also tends to come with a lower credit risk premium, reminiscent of a decreasing equilibrium risk price in the model.

Finally, Table 10 provides suggestive evidence that movements in growth potential relative to collateral is related to the pricing of risk across asset classes. The first panel verifies the well known pattern that patent measures predict stock returns over longer horizons. The remaining panels are more suggestive in the sense that they rely on measures of returns that use, as discussed in the data section, internal rates of returns in the VC and the buyout industry. Those returns tend to be positively, and sometimes significantly forecasted by proxies for the IC ratio. Additionally, the latter has some predictive power for long-term corporate returns.

5 Conclusion

We describe and quantitatively examine a general equilibrium asset pricing model in which the transformation of stochastically arriving blueprints into patents creates collateral value that productive firms can borrow against. This slow adoption gives rise to leverage and collateral cycles correlated with, but distinct from standard business cycles. New blueprints are quickly capitalized into stock markets, but into corporate bond markets only with an adoption lag, so that relative valuations can temporarily diverge. When new blueprints are abundant, uncertainty about the pace of future successful adoptions is high, which is reflected in a high market price of risk and low collateral values. Conversely, in the aftermath of successful adoption waves, firms lever up to exploit tax benefits while the equilibrium price of risk falls. Expected returns in the model thus depend on the stage of the credit cycle, are predictable, and reflect endogenously time-varying exposures and risk prices. Empirically, we find evidence that measures of new blueprints, such as patents, relative to collateral predict lower credit spreads and credit risk premia, and higher leverage going forward, consistent with model predictions.

We provide an interpretation of innovation driven credit cycles in the context of the private equity industry. In line with our model, the high returns on equity-like VC investments during the tech boom coincided with elevated levels of volatility, as captured by the VIX, while the buyout booms preceeding the great recession coincided with episodes of low corporate bond risk premia, and elevated leverage. Remarkably, we find evidence that in the data, the ratio of patent applications to collateral has predictive power for buyout activity in the medium run.

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7 Appendix

7.1 Model

Shareholder Optimization For completeness, we include the full solution to shareholders' optimization problem. Conditional on survival in the current period, the recursive representation of the Lagrangian for the shareholders' problem is:

$$\begin{aligned} L_t = & (1-\tau)(y_t - i_t - w_t l_t - \int_0^{A_t} P_{i,t} X_{i,t} di - z_{i,t}\bar{k}_t) \\ & + q_t b_{t+1} - (1 + (1-\tau)C) b_t - \psi(b_t, b_{t+1}) \\ & + \Lambda_t ((1-\delta) k_t + \Gamma(\frac{i_t}{k_t}) k_t - k_{t+1}) \\ & + E_t M_{t,t+1} \int_{\underline{z}}^{\bar{z}} L_{t+1} d\Phi(z_{t+1}) \end{aligned} \tag{12}$$

The first order conditions with respect to i_t, l_t, $X_{i,t}$, k_{t+1} and b_{t+1} are:

$$i_t : \; 1 - \tau = \Lambda_t \Gamma'_t \tag{13}$$

$$l_t : \; w_t = (1-\alpha)(1-\xi) y_t \tag{14}$$

$$X_{i,t} : \; \xi y_t G_t^{-\frac{1}{\nu}} X_{i,t}^{\frac{1}{\nu}-1} - P_{i,t} = 0 \tag{15}$$

$$k_{t+1} : \; q'_{k_{t+1},t} b_{t+1} - \Lambda_t + E_t M_{t+1} \int_{\underline{z}}^{z^*_{t+1}} L'_{k_{t+1},t+1} d\Phi(z_{t+1}) = 0 \tag{16}$$

$$b_{t+1} : \; q'_{b_{t+1},t} b_{t+1} + q_{t+1} - \psi_{b_{t+1},t} + E_t M_{t+1} \int_{\underline{z}}^{z^*_{t+1}} L'_{b_{t+1},t+1} d\Phi(z_{t+1}) = 0 \tag{17}$$

The envelope condition is:

$$L'_{k,t} = \frac{\partial L_t}{\partial k_t} = (1-\tau)\alpha(1-\xi)\frac{y_t}{k_t} + \Lambda_t((1-\delta) - \Gamma'_t(\frac{i_t}{k_t}) + \Gamma) \tag{18}$$

$$L'_{b_t,t} = \frac{\partial L_t}{\partial b_t} = -((1-\tau)C+1) - \psi'_{b_t} \tag{19}$$

Since the value of the debt is:

$$q_t b_{t+1} = E_t M_{t,t+1} \left\{ \Phi(z^*_{t+1})(C+1)b_{t+1} + (1-\Xi) \int_{z^*_{t+1}}^{\bar{z}} V(0, k_{t+1}, z_{t+1}) d\Phi(z_{t+1}) \right\}$$

So we have:

$$q'_{k_{t+1},t} b_{t+1} = E_t M_{t,t+1} \left[z^{*'}_{k_{t+1},t+1} \phi(z^*_{t+1}) b_{t+1} (\tau C + \Xi[(1-\tau)C+1]) + (1-\Xi) \int_{z^*_{t+1}}^{\bar{z}} L'_{k_{t+1},t+1} d\Phi(z_{t+1}) \right] \tag{20}$$

$$q'_{b_{t+1},t} b_{t+1} + q_t = E_t M_{t,t+1} [(C+1)\Phi(z^*_{t+1}) + z^{*'}_{b_t,t} \phi_z(z^*_{t+1}) b_{t+1} (\tau C + \Xi((1-\tau) * C + 1))] \tag{21}$$

where:

$$z^*_t = \frac{L_t}{(1-\tau)\bar{k}_t}$$

$$z^{*'}_{k_t,t} = \frac{L'_{k,t}}{(1-\tau)\bar{k}_t}$$

$$z^{*'}_{b_t,t} = \frac{L'_{b,t}}{(1-\tau)\bar{k}_t}$$

Bond Excess Premium The log credit spread can be approximated by

$$\log cs_t \approx p_{neu,t} - \chi_{rec,t}$$

where

$$\begin{aligned} p_{neu,t} &= E_t \left[\frac{M_{t+1}}{E_t[M_{t+1}]} \int_{z^*_{t+1}}^{\bar{z}} d\Phi(z_{t+1}) \right] \\ &= E_t \left[\frac{M_{t+1}}{E_t[M_{t+1}]} (1 - \Phi(z^*_{t+1})) \right] \end{aligned}$$

so $p_{neu,t}$ is the risk-neutral default probability And

$$\chi_{rec,t} = E_t M_{t,t+1} \left\{ \int_{z^*_{t+1}}^{\bar{z}} R_{rec,t+1}(z_{t+1}) d\Phi(z_{t+1}) \right\}$$

so $\chi_{rec,t}$ is the value of the recovery rate which is defined by:

$$R_{rec,t+1}(z_{t+1}) = \frac{(1-\Xi)V_{final}(0, k_{t+1}, z_{t+1})}{q_t b_{t+1}}$$

We can rewrite the $\log cs_t$:

$$\begin{aligned}
\log cs_t &\approx E_t \left[\frac{M_{t+1}}{E_t[M_{t+1}]} \int_{z^*_{t+1}}^{\bar{z}} d\Phi(z_{t+1}) \right] - E_t M_{t,t+1} \left\{ \int_{z^*_{t+1}}^{\bar{z}} R_{rec,t+1}(z_{t+1}) d\Phi(z_{t+1}) \right\} \\
&= E_t M_{t,t+1} \left\{ \int_{z^*_{t+1}}^{\bar{z}} (R_{f,t} - R_{rec,t+1}(z_{t+1})) d\Phi(z_{t+1}) \right\} \\
&= \frac{E_t \left[\int_{z^*_{t+1}}^{\bar{z}} (R_{f,t} - R_{rec,t+1}(z_{t+1})) d\Phi(z_{t+1}) \right]}{R_{f,t}} + Cov_t(M_{t+1}, \int_{z^*_{t+1}}^{\bar{z}} (R_{f,t} - R_{rec,t+1}(z_{t+1})) d\Phi(z_{t+1}))
\end{aligned}$$

The first term is the expected losses in default and the second term is a risk premium. We refers the second term as bond excess premium.

$$\text{bond excess premium} = Cov_t(M_{t+1}, \int_{z^*_{t+1}}^{\bar{z}} (R_{f,t} - R_{rec,t+1}(z_{t+1})) d\Phi(z_{t+1})) \tag{22}$$

7.2 Empirics

Regressions We run the following forecasting regression for dependent variablesother than buy-out values and buyout volumes

$$\frac{1}{n} \sum_{i=0}^{n-1} CreditMeasures_{t+1+i} = \mu + InnovationMeasures_t + \epsilon_{a,t+1}$$

where n is the year horizon. When we only have annual data for the independent variables, such as for the empirical proxies for $Patents_t/K_t$, we convert monthly and quarterly variables to annual frequency, by taking averages. For monthly data, for example, at year t, we compute $Measure_t = \frac{\sum_{i=1}^{12} Mon_i}{12}$, and for quarterly data, we compute, at year t, $Measure_t = \frac{Q1+Q2+Q3+Q4}{4}$.

Data Description The variables in the dataset are defined as follows:

total_app: Patent Applications. Patent data are from U.S. Patent Trademark Office. In our sample, the annual data series are from 1840 to 2013. The total patent applications and total issued patents are accumulated from in-force and issued patents by NBER sub-category in each year. See Marco, Alan C. and Carley, Michael and Jackson, Steven and Myers, Amanda F., The USPTO Historical Patent Data Files: Two Centuries of Innovation (June 1, 2015) for further details.

produced_fixed_assets_private: Private Capital (K_t): Capital stock data are from the NIPA table 5.10. Only fixed assets (structures, equipment, and intellectual property products) are considerd. Inventories are not included in the measurement.

ebp_oa: Excess bond premium. The data series is option adjusted.

gz spr: GZ credit spread. Senior unsecured corporate bond cross-sectional average credit spread. Only nonfinancial firms.

QL: Market Leverage.

BL: Book Leverage.

assetvalue: The asset-based buyout activity measures.

aaa10ym and baa10ym: Moodys Seasoned Aaa/Baa Corporate Bond Yield Spreads (relative to the 10-year Treasury Constant Maturity).

CCG: Corporate Credit Growth which is constructed by $\frac{DebtIssuance}{BusinessGDP}$

Log Mrk Return: Log market returns.

Log Risk-Free Rate: Log risk-free rate.

vc_irr: vc index returns. (Source: Cambridge Associates)

buyout_irr: buyout index returns. (Source: Cambridge Associates)

LTCRPBD: Long Term Corporate Bond Returns. (Source: Ibbotson)

Table 1
Benchmark Calibration

Preferences		
Relative Risk Aversion	(γ)	10
Intertemporal Elasiticity of Substitution	(ψ)	2
Subjective Discount Rate	(β)	$0.984^{1/4}$
Production		
Capital Share	(α)	0.35
Private Capital Depreciation Rate	(δ_k)	0.08/4
Investment Adjustment Cost Elasticity	(ζ)	7
Patent Share	(ξ)	0.5
Markup	(ν)	1.65
Innovation and *R&D*		
Patent Survival Rate	(ϕ)	0.9625
Adoption Scale Parameter	(Λ)	0.461
Adoption Elasticity Parameter	(κ)	0.8
Technological Innovation Scale Parameter	($\bar{\chi}$)	0.0425
Technological Innovation Elasticity Parameter	(ξ^*)	0.6
Debt		
Coupon payment	(C)	0.01/4
Bankruptcy costs	(Ξ)	0.123
Volatility Idiosyncratic Shock	(σ_z)	0.3166
Corporate tax rate	(τ)	0.1376
Debt adjustment cost parameter	(χ_b)	0.35
Productivity		
Unconditional Growth	(μ)	0.02/4
Volatility of Productivity Shock	(σ_a)	0.06/2
Volatility of Innovation Shock	(σ_x/σ_a)	0.28
Productivity Persistence	(ρ)	$0.95^{1/4}$
Innovation Persistence	(ρ_v)	$0.973^{1/4}$

Notes: This table reports our quarterly calibration.

Table 2
Basic Quantitative Moments

A. Macro Moments	
$\sigma(\Delta y)$ (%)	3.62
$\sigma(\Delta c)/\sigma(\Delta y)$	0.67
$E[I/Y]$ (%)	17.06
$\sigma(\Delta i)/\sigma(\Delta y)$	1.77
$\rho(\Delta c, \Delta i)$	0.87
$ACF(\Delta c)$	0.58
$\rho(B/K, \Delta y)$	0.11
B. Asset Pricing Moments	
$E[r_{ex,k}]$ (%)	3.28
$\sigma(r_{ex,k})$ (%)	11.86
$E[r_{ex,a}]$ (%)	0.18
$\sigma(r_{ex,a})$ (%)	1.38
$E[r_{ex,t}]$ (%)	7.24
$\sigma(r_{ex,t})$ (%)	12.97
$E[r_{ex,c}]$ (%)	0.01
$\sigma(r_{ex,c})$ (%)	0.03
$E\left[r^f\right]$ (%)	1.89
$\sigma(r^f)$ (%)	0.70
C. Credit Market Moments	
$E[cs]$ (bps)	79.99
$\sigma(cs)$ (bps)	24.68
$\rho(cs, \Delta y)$	-0.32

Notes: This table reports simulated moments for the benchmark calibration. Δy is the growth rate of the final good output. Δc is the growth rate of the aggregate consumption. Δi is the growth rate of the aggregate investment. Growth rate moments are in annualized percentage units. Y, C, I, B/K are aggregate output, consumption, investment, and book leverage, respectively. $r_{ex,k}$ is the excess return on the final good firm. $r_{ex,a}$ is the excess return on adoption. $r_{ex,c}$ is the excess return on corporate bonds. $r_{ex,t}$ is the excess return on stock market. cs is the credit spread. Returns are in annualized percentage units, unless indicated otherwise.

Table 3
Return Predictability: IC

Variables	Independent Variable: Z_t/K_t Horizon (Year) 1	2	3	4	5
Excess Return on Final Firm					
$\beta^{(n)}$	3.7024	4.1628	4.6487	5.1427	5.6302
t-stats	3.2019	3.5457	3.8813	4.2020	4.5010
Adjusted R^2	0.0334	0.0362	0.0400	0.0453	0.0521
Excess Return on Adoption					
$\beta^{(n)}$	0.4048	0.4022	0.3998	0.3979	0.3950
t-stats	3.4435	4.6152	5.5305	6.3115	6.9752
Adjusted R^2	0.0331	0.0615	0.0863	0.1089	0.1296
Excess Return on Stock Market					
$\beta^{(n)}$	0.2949	0.3021	0.3093	0.3169	0.3228
t-stats	1.5697	2.1232	2.5662	2.9566	3.2912
Adjusted R^2	0.0254	0.0449	0.0605	0.0740	0.0859
Excess Return on Corporate Bond					
$\beta^{(n)}$	0.0016	0.0016	0.0016	0.0016	0.0016
t-stats	0.6237	0.8370	1.0072	1.1612	1.2894
Adjusted R^2	0.0122	0.0218	0.0300	0.0373	0.0438

Notes: This table reports excess stock return forecasts in simulated data for horizons of one to five years using the IC ratio: $r^{ex}_{t,t+n} = \alpha_n + \beta Z_t/K_t + \epsilon_{t+n}$. The estimates from the model regression are averaged across 100 simulations.

Table 4
Return Predictability: Sensitivity

Variables	Independent Variable: Z_t/K_t Horizon (Year) 1	2	3	4	5
Excess Return on Final Firm					
$\beta^{(n)}$	3.7024	4.1628	4.6487	5.1427	5.6302
t-stats	3.2019	3.5457	3.8813	4.2020	4.5010
Adjusted R^2	0.0334	0.0362	0.0400	0.0453	0.0521
Excess Return on Final Firm: High Tax Rate/Leverage					
$\beta^{(n)}$	2.1254	3.2953	4.4382	5.6227	6.7913
t-stats	3.4255	3.7462	4.0846	4.4520	4.7989
Adjusted R^2	0.0372	0.0411	0.0450	0.0496	0.0551
Excess Return on Final Firm: Instantaneous Diffusion					
$\beta^{(n)}$	1.7314	1.9247	2.1518	2.3693	2.5829
t-stats	1.2216	1.4328	1.6562	1.8489	2.0625
Adjusted R^2	0.0292	0.0314	0.0340	0.0361	0.0402

Notes: This table reports excess stock return forecasts in simulated data for horizons of one to five years using the log-price-dividend ratio: $r^{ex}_{t,t+n} = \alpha_n + \beta Z_t/K_t + \epsilon_{t+n}$. P_t is the price of the equity market. The estimates from the model regression are averaged across 100 simulations.

Table 5
Stock Return Predictability: Conditional Return Volatility

Variables	Independent Variable: $\sigma_t(m_{t+1})$ Horizon (Year) 1	2	3	4	5
Excess Return on Final Firm					
$\beta^{(n)}$	-0.1559	-0.2146	-0.2351	-0.2195	-0.1822
t-stats	-0.6234	-0.9837	-1.1825	-1.1553	-0.9599
Adjusted R^2	0.1442	0.1983	0.2273	0.2481	0.2426
Excess Return on Adoption					
$\beta^{(n)}$	0.1301	0.1468	0.1585	0.1462	0.1264
t-stats	0.7985	1.2868	1.8232	2.0271	2.0213
Adjusted R^2	0.0557	0.1298	0.1859	0.2061	0.2095
Excess Return on Stock Market					
$\beta^{(n)}$	0.1442	0.1717	0.1942	0.1823	0.1607
t-stats	0.5589	0.9416	1.3798	1.5577	1.5800
Adjusted R^2	0.0627	0.1426	0.2022	0.2267	0.2307

Notes: This table reports forecasts in the long sample for horizons of one to five years using the conditional volatility of the stochastic discount factor: $r_{t,t+n} = \alpha_n + \beta\sigma_t(m_{t+1}) + \epsilon_{t+n}$. The estimates from the model regression are averaged across 100 simulations.

Table 6
Discount Rates and Credit Markets

	Independent Variable:$\sigma_t(m_{t+1})$				
	Horizon (Year)				
Variables	1	2	3	4	5
Credit Spread					
$\beta^{(n)}$	0.0379	0.0320	0.0250	0.0192	0.0138
t-stats	2.1373	1.8182	1.4680	1.1935	0.9029
Adjusted R^2	0.2026	0.2193	0.2525	0.2906	0.3182
Excess Bond Premium					
$\beta^{(n)}$	0.0090	0.0094	0.0093	0.0086	0.0074
t-stats	2.3077	2.4467	2.4981	2.4214	2.1464
Adjusted R^2	0.2435	0.2557	0.2579	0.2579	0.2657
Book Leverage					
$\beta^{(n)}$	-0.0056	-0.0057	-0.0054	-0.0048	-0.0040
t-stats	-2.4030	-2.4127	-2.2985	-2.1170	-1.8016
Adjusted R^2	0.2493	0.2513	0.2547	0.2658	0.2813
Market Leverage					
$\beta^{(n)}$	-0.0061	-0.0065	-0.0065	-0.0060	-0.0052
t-stats	-2.2973	-2.4940	-2.5474	-2.4491	-2.1496
Adjusted R^2	0.2538	0.2603	0.2586	0.2576	0.2623

Notes: This table reports forecasts of credit variables in simulated data for horizons of one to five years using the specification: $\frac{1}{n}\sum_{i=0}^{n-1} CreditMeasures_{t+1+i} = \alpha_n + \beta\sigma_t(m_{t+1}) + \epsilon_{t+n}$. Standard errors are Newey West adjusted. The estimates from the model regression are averaged across 100 simulations.

Table 7
Credit Market Predictability

	Independent Variable: Z_t/K_t Horizon (Year)			
Variables	5	6	7	8
Credit Spread				
$\beta^{(n)}$	-3.6974	-4.8975	-6.0110	-7.0447
t-stats	-1.7588	-2.3773	-2.9820	-3.5768
Adjusted R^2	0.0444	0.0512	0.0593	0.0684
Excess Bond Premium				
$\beta^{(n)}$	-0.5883	-0.9563	-1.3063	-1.6364
t-stats	-1.0366	-1.7116	-2.3811	-3.0447
Adjusted R^2	0.0513	0.0575	0.0654	0.0750
Book Leverage				
$\beta^{(n)}$	0.4304	0.6830	0.9221	1.1468
t-stats	1.2223	1.9628	2.6893	3.4028
Adjusted R^2	0.0371	0.0425	0.0499	0.0589
Market Leverage				
$\beta^{(n)}$	0.2539	0.5435	0.8193	1.0797
t-stats	0.6552	1.4182	2.1684	2.9059
Adjusted R^2	0.0349	0.0389	0.0449	0.0529

Notes: This table reports forecasts of credit variables in simulated data for horizons of four to eight years using the specification: $\frac{1}{n}\sum_{i=0}^{n-1} CreditMeasures_{t+1+i} = \mu + Z_t/K_t + \epsilon_{a,t+1}$. Standard errors are Newey West adjusted. The estimates from the model regression are averaged across 100 simulations.

Table 8
Data: Credit Market Predictability

Variables		Horizon (Year) 5	6	7	8
		Panel A: Independent Variable: ZK_{nom}			
Market Leverage	$\beta^{(n)}$	0.0114	0.0112	0.0111	0.0114
		(3.0256)	(3.1650)	(3.2332)	(3.1599)
	Adjusted R^2	0.1245	0.1141	0.1073	0.1081
Book Leverage	$\beta^{(n)}$	0.0193	0.0208	0.0214	0.0229
		(1.8286)	(2.0828)	(2.3619)	(2.9077)
	Adjusted R^2	0.1774	0.1616	0.1801	0.2124
Credit Growth	$\beta^{(n)}$	0.0092	0.0088	0.0076	0.0058
		(2.0316)	(2.3211)	(2.4560)	(1.9032)
	Adjusted R^2	0.0968	0.1081	0.1014	0.0546
Buyout Value	$\beta^{(n)}$	0.0853	0.3181	0.6065	0.4948
		(0.2562)	(1.2688)	(1.8246)	(0.8124)
	Adjusted R^2	-0.0421	-0.0270	0.0135	-0.0093
		Panel B: Independent Variable: ZK_{lin}			
Market Leverage	$\beta^{(n)}$	0.2964	0.5828	0.7295	0.8835
		(0.4940)	(0.8182)	(1.0361)	(1.2390)
	Adjusted R^2	0.0251	0.0018	0.0179	0.0391
Book Leverage	$\beta^{(n)}$	0.5710	0.6815	0.6967	0.6558
		(0.5545)	(0.5779)	(0.6118)	(0.5658)
	Adjusted R^2	0.0210	0.0185	0.0178	0.0218
Credit Growth	$\beta^{(n)}$	0.4234	0.4268	0.4203	0.3216
		(1.2195)	(1.4773)	(2.0482)	(1.7790)
	Adjusted R^2	0.0195	0.0305	0.0631	0.0414
Buyout Value	$\beta^{(n)}$	55.2909	67.1942	86.1621	48.3097
		(1.2284)	(1.4658)	(2.3599)	(1.0817)
	Adjusted R^2	0.0720	0.1060	0.1966	0.0263
		Panel C: Independent Variable: ZK_{HP}			
Market Leverage	$\beta^{(n)}$	1.9900	1.7470	1.4216	1.1767
		(3.2088)	(2.8923)	(2.4698)	(2.0191)
	Adjusted R^2	0.1483	0.1074	0.0662	0.0334
Book Leverage	$\beta^{(n)}$	0.7385	0.4715	0.1004	-0.1478
		(0.7364)	(0.4695)	(0.1045)	(-0.1459)
	Adjusted R^2	0.1569	0.1969	0.2331	0.2749
Credit Growth	$\beta^{(n)}$	-0.6358	-0.5624	-0.3517	-0.3869
		(-1.1063)	(-1.2158)	(-0.8790)	(-1.2849)
	Adjusted R^2	0.0193	0.0254	-0.0007	0.0314
Buyout Value	$\beta^{(n)}$	-48.6801	-51.7355	-36.8658	-75.3498
		(-1.1302)	(-1.4710)	(-1.0373)	(-1.3647)
	Adjusted R^2	0.0078	0.0162	-0.0205	0.0545

Notes: This table reports forecasts of credit variables for horizons of five to eight years using the specification: $\frac{1}{n}\sum_{i=0}^{n-1} CreditMeasures_{t+1+i} = \mu + Z_t/K_t + \epsilon_{a,t+1}$. T-stats are in parentheses. ZK_{nom} are patent applications deflated by the nominal capital stock, ZK_{lin} is linearly detrended real Z/K, and ZK_{HP} is Z/K detrended with a one-sided HP filter. Standard errors are Newey West adjusted. Credit measures are i) market leverage (sample: 1980-2014), ii) book leverage (sample: 1980-2014), iii) credit growth (sample: 1983-2014), and iv) buyout value (sample: 1983-2011)

Table 9
Data: Credit Spread Predictability

Variables		Horizon (Year) 5	6	7	8
		Panel A: Independent Variable: ZK_{nom}			
GZ Credit Spread	$\beta^{(n)}$	-0.5787	-0.5802	-0.4658	-0.3295
		(-5.4637)	(-5.3603)	(-3.3300)	(-1.7441)
	Adjusted R^2	0.4554	0.4069	0.2374	0.0739
GZ Excess Bond Premium	$\beta^{(n)}$	-0.1215	-0.1313	-0.0726	-0.0213
		(-2.9463)	(-4.3514)	(-1.9517)	(-0.5793)
	Adjusted R^2	0.1581	0.2806	0.1108	-0.0289
Baa Spread	$\beta^{(n)}$	-0.3754	-0.3295	-0.2289	-0.0728
		(-3.8365)	(-3.0916)	(-1.7156)	(-0.5305)
	Adjusted R^2	0.3641	0.2769	0.0919	-0.0372
		Panel B: Independent Variable: ZK_{lin}			
GZ Credit Spread	$\beta^{(n)}$	–20.3327	-13.5733	-1.6450	12.9587
		(-1.6824)	(-0.9176)	(-0.1127)	(0.9514)
	Adjusted R^2	0.0859	0.0091	-0.0426	0.0069
GZ Excess Bond Premium	$\beta^{(n)}$	-9.9791	-10.7750	-6.1429	-2.4137
		(-2.9572)	(-4.2714)	(-2.1533)	(-0.9447)
	Adjusted R^2	0.2352	0.4071	0.2221	0.0148
Baa Spread	$\beta^{(n)}$	-13.8676	-7.0069	2.1887	10.4780
		(-1.3826)	(-0.8527)	(0.3282)	(1.6578)
	Adjusted R^2	0.0901	-0.0041	-0.0431	0.0604
		Panel C: Independent Variable: ZK_{HP}			
GZ Credit Spread	$\beta^{(n)}$	-58.1445	-58.6593	-52.8986	-43.1883
		(-4.7861)	(-5.2200)	(-4.9736)	(-3.7902)
	Adjusted R^2	0.4152	0.4658	0.4553	0.3116
GZ Excess Bond Premium	$\beta^{(n)}$	-9.0700	-11.0042	-7.8179	-4.4430
		(-2.2645)	(-3.9792)	(-2.9487)	(-1.4885)
	Adjusted R^2	0.0605	0.2087	0.2030	0.0798
Baa Spread	$\beta^{(n)}$	-0.32.3057	-32.8981	-29.8592	-23.8168
		(-3.5770)	(-4.8836)	(-4.6014)	(-3.2282)
	Adjusted R^2	0.3720	0.5140	0.4590	0.2710

Notes: This table reports forecasts of credit variables for horizons of five to eight years using the specification: $\frac{1}{n}\sum_{i=0}^{n-1} CreditMeasures_{t+1+i} = \mu + Z_t/K_t + \epsilon_{a,t+1}$. T-stats are in parentheses. ZK_{nom} are patent applications deflated by the nominal capital stock, ZK_{lin} is linearly detrended real Z/K, and ZK_{HP} is Z/K detrended with a one-sided HP filter. Credit measures are i) GZ credit spread (i.e. The average (cross-sectional) credit spread on senior unsecured corporate bonds issued by nonfinancial firms, sample: 1983-2014), ii) (option-adjusted) GZ excess bond premium (sample: 1983-2014), iii) market leverage (sample: 1980-2014), and iii) Baa Spread (sample: 1983-2011)

Table 10
Data: Return Predictability

Variables		Horizon (Year) 5	6	7	8
Panel A: Independent Variable: ZK_{nom}					
Market Excess Returns	$\beta^{(n)}$	0.0409	0.0370	0.0260	0.0173
		(4.2054)	(3.9918)	(1.6612)	(0.9777)
	Adjusted R^2	0.1900	0.2132	0.0687	-0.0050
VC Index Returns	$\beta^{(n)}$	8.7951	9.3160	9.2984	9.6228
		(1.9893)	(2.3254)	(2.1873)	(1.8547)
	Adjusted R^2	0.0351	0.0376	0.0344	0.0282
Buyout Index Returns	$\beta^{(n)}$	3.5840	4.1151	2.8421	1.7991
		(2.6771)	(5.2171)	(2.5390)	(1.3835)
	Adjusted R^2	0.1935	0.3752	0.2350	0.0640
Long-term Corporate Bond Returns	$\beta^{(n)}$	0.0032	0.0026	0.0032	0.0034
		(1.1998)	(1.1179)	(1.4041)	(1.3488)
	Adjusted R^2	0.0577	0.0362	0.0705	0.0552
Panel B: Independent Variable: ZK_{lin}					
Market Excess Returns	$\beta^{(n)}$	1.8809	1.2060	0.0419	-0.6513
		(1.8043)	(1.3622)	(0.0391)	(-0.5867)
	Adjusted R^2	0.0597	0.0220	-0.0454	-0.0265
VC Index Returns	$\beta^{(n)}$	777.0023	827.1187	746.5491	666.4748
		(1.7480)	(1.9007)	(1.6062)	(1.2871)
	Adjusted R^2	0.0806	0.0875	0.0771	0.0561
Buyout Index Returns	$\beta^{(n)}$	256.6964	285.9752	159.8842	62.7729
		(2.4899)	(4.6759)	(2.0480)	(0.7592)
	Adjusted R^2	0.2166	0.3782	0.1648	-0.0154
Long-term Corporate Bond Returns	$\beta^{(n)}$	-0.0798	-0.1822	-0.1625	-0.2007
		(-0.6914)	(-1.9823)	(-1.7913)	(-2.2906)
	Adjusted R^2	-0.0272	0.0278	0.0183	0.0408
Panel C: Independent Variable: ZK_{HP}					
Market Excess Returns	$\beta^{(n)}$	3.8782	3.8241	2.9630	2.7548
		(3.6923)	(5.9305)	(2.9095)	(2.2490)
	Adjusted R^2	0.1889	0.3337	0.2121	0.1823
VC Index Returns	$\beta^{(n)}$	-85.8012	20.3772	217.7214	374.9092
		(-0.2239)	(0.0590)	(0.8004)	(1.3211)
	Adjusted R^2	-0.0009	0.0079	0.0105	-0.0145
Buyout Index Returns	$\beta^{(n)}$	237.8483	292.6833	223.2571	155.6164
		(2.3255)	(3.7374)	(2.9853)	(1.8154)
	Adjusted R^2	0.0561	0.2081	0.2143	0.1179
Long-term Corporate Bond Returns	$\beta^{(n)}$	0.2697	0.1717	0.1772	0.1357
		(1.8507)	(1.7854)	(2.4357)	(1.5287)
	Adjusted R^2	0.0178	-0.0080	-0.0009	-0.0198

*Notes:*This table reports forecasts of various returns for horizons of five to eight years using the specification. T-stats are in parentheses. ZK_{nom} are patent applications deflated by the nominal capital stock, ZK_{lin} is linearly detrended real Z/K, and ZK_{HP} is Z/K detrended with a one-sided HP filter. Returns are i) market excess returns (sample: 1983-2012), ii) VC index returns (sample: 1983-2014), iii) buyout index returns (sample: 1987-2014), and iv) long-term bond returns (sample: 1982-2013)

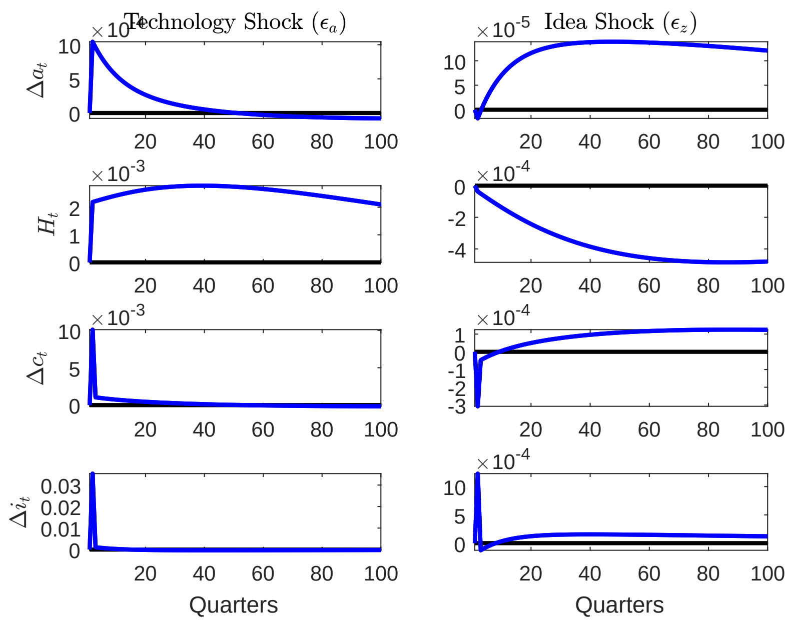

Figure 1

Impulse Responses. This figure shows percentage deviations from steady state. Our benchmark calibration is reported in table 1.

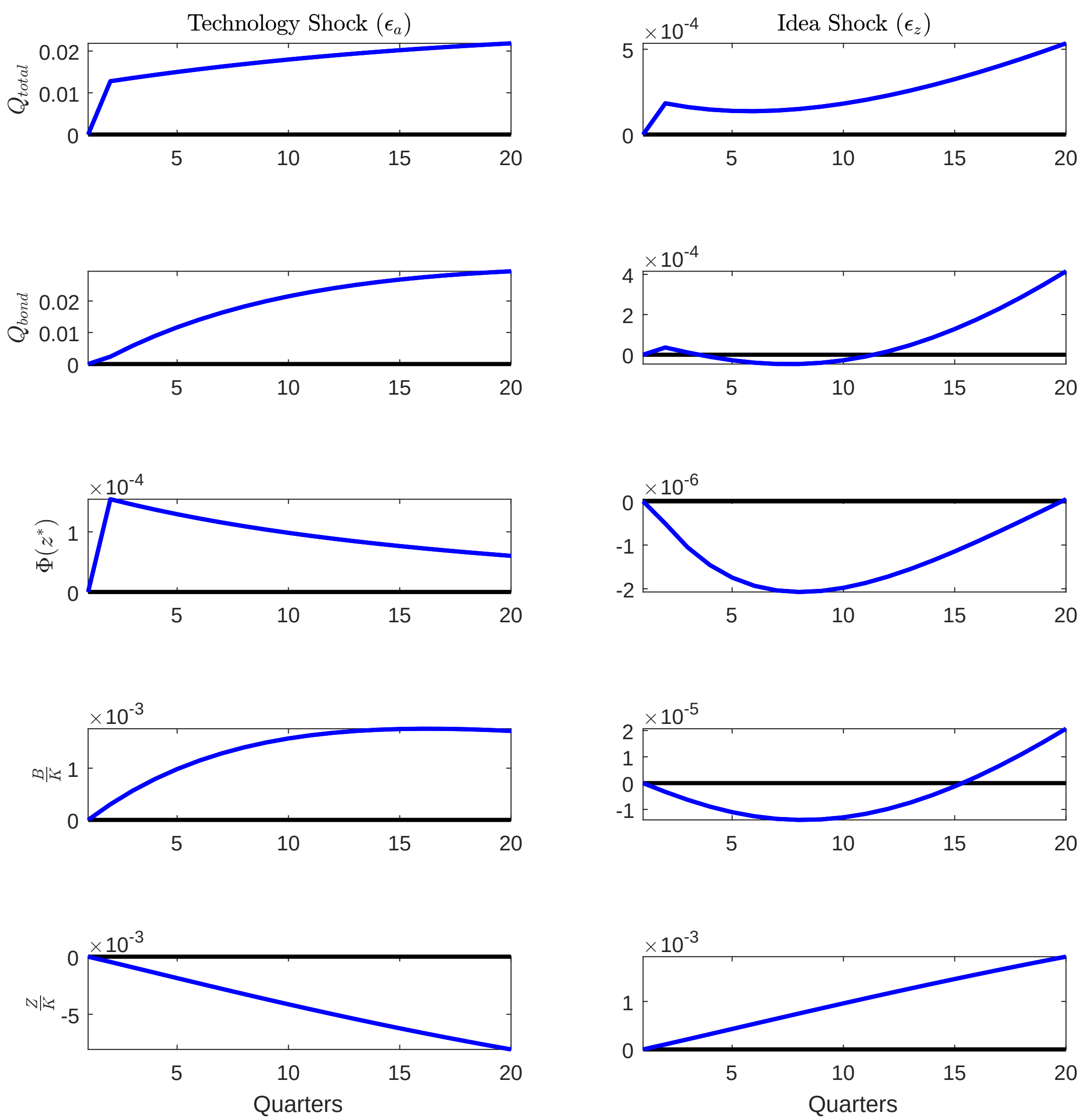

Figure 2
Impulse Responses. This figure shows percentage deviations from steady state. Our benchmark calibration is reported in table 1.

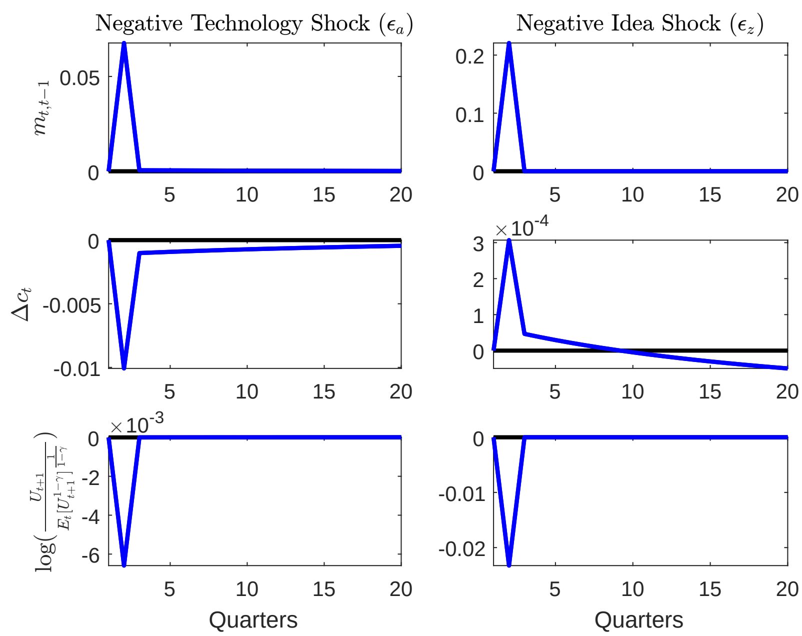

Figure 3

Impulse Responses. This figure shows percentage deviations from steady state with respect to negative technology shock and negative idea shock. Our benchmark calibration is reported in table 1.

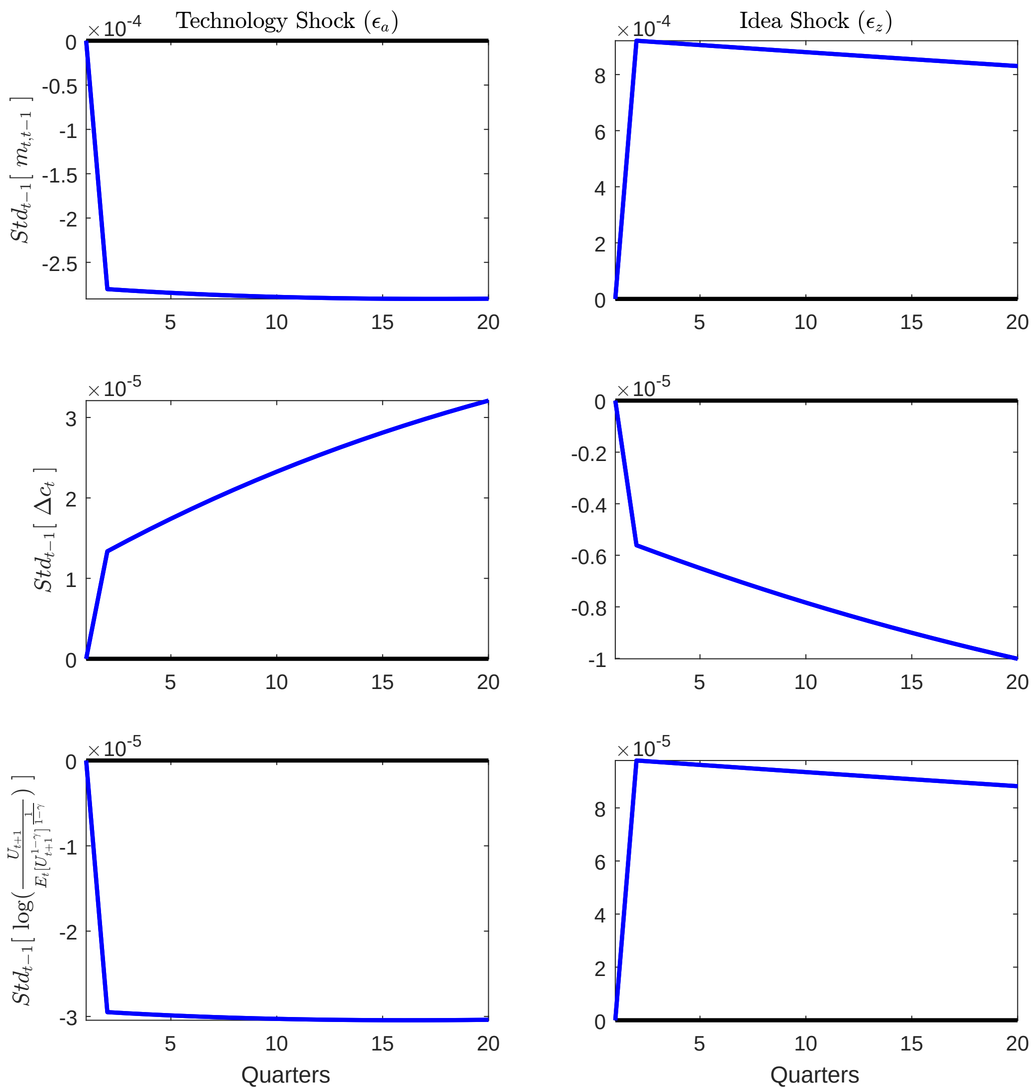

Figure 4

Impulse Responses. This figure shows percentage deviations from steady state. Our benchmark calibration is reported in table 1.

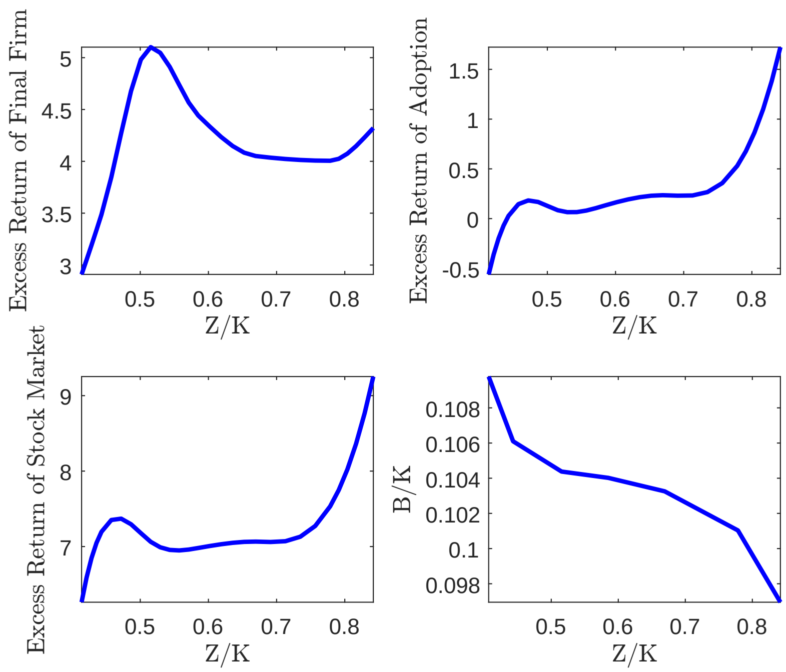

Figure 5
Conditional excess returns areplotted against the underlying Z/K.

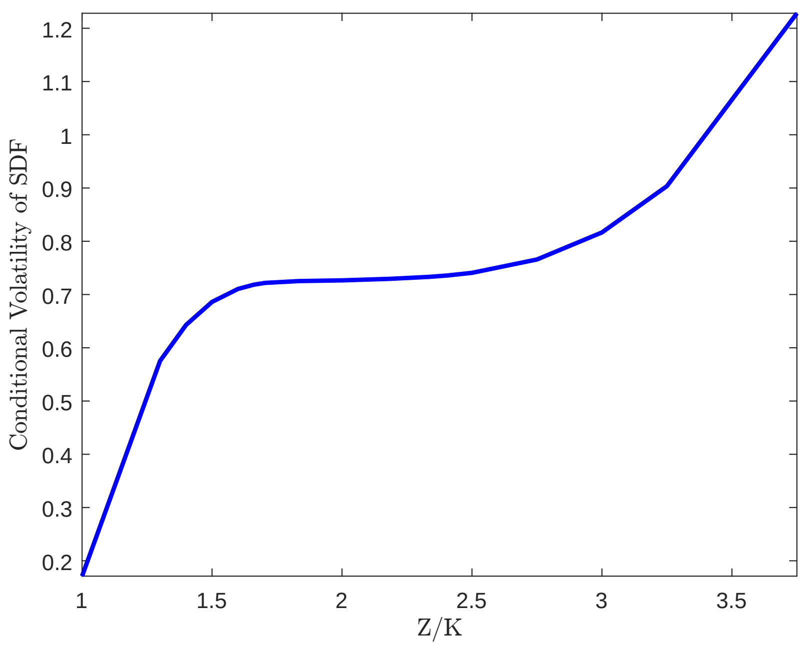

Figure 6
The conditional volatility of the SDF is plotted against the underlying Z/K.

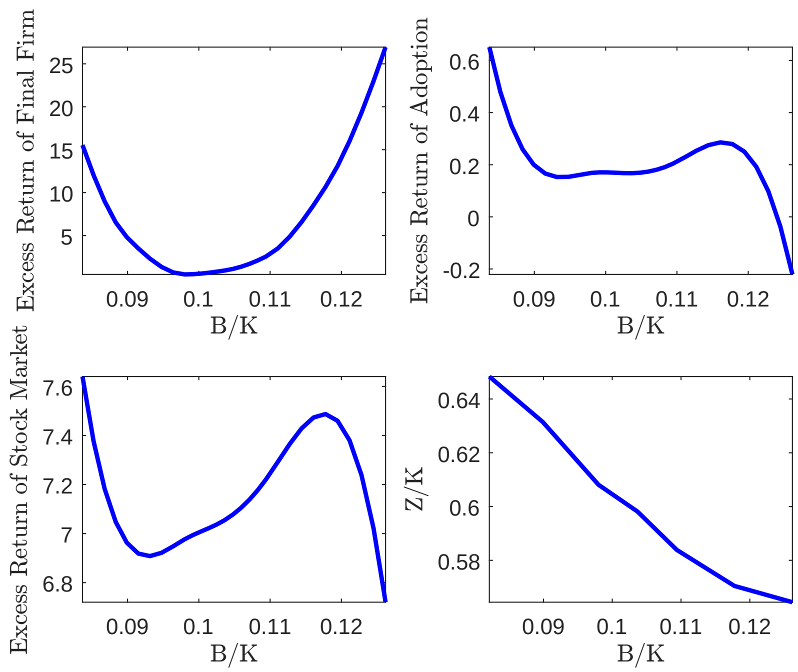

Figure 7
Conditional excess returns areplotted against the underlying B/K.

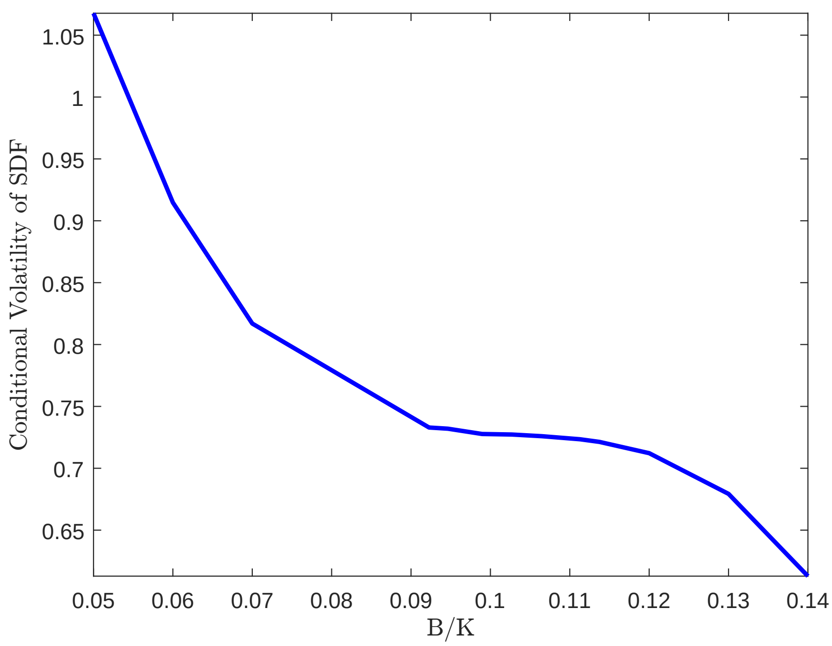

Figure 8
The conditional volatility of the SDF is plotted against the underlying B/K.