Financial Frictions on Capital Allocation: A Transmission Mechanism of TFP Fluctuations*

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Abstract

This paper provides a theory of financial frictions as a transmission mechanism for primitive shocks to translate into aggregate TFP fluctuations. In our model, financial frictions distort existing capital allocation across different production units, rather than investment in new capital. News shocks on future technology improvement are introduced as a device to identify TFP fluctuations originating from this mechanism. Our simulation shows that variations in financial frictions in response to news shocks can generate sizable fluctuations in aggregate TFP and, thus, business cycles before the actual technology change is realized. Using a combined dataset from COMPUSTAT and IBES, we find that the empirical responses of capital acquisition to prospects about future profitability are significantly larger for firms more likely to be financially constrained, while such a pattern does not exist for new capital investment. Furthermore, capital acquisition of constrained firms is found to be more procyclical than that for unconstrained ones. Our evidence thus provides strong support for the importance of financial frictions on capital allocation as the transmission mechanism proposed by our theory.

JEL Classification: E32, G34

Keywords: Financial Friction, Capital Reallocation, TFP Fluctuation, News Shock

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1 Introduction

Macroeconomists have long searched for factors behind aggregate Total Factor Productivity (TFP). In particular, a theory of TFP fluctuations has been called for, due to their key role in business cycles.[1] One promising candidate for understanding TFP fluctuations is financial friction on inputs. The presence of such friction naturally distorts resource allocation and, thus, reduces aggregate productive efficiency. In fact, the business cycle literature has long emphasized the distortion by financial frictions on new capital investment. Recent evidence, however, points to a different channel for financial frictions to affect resource allocation: distorting existing capital allocation across firms. For example, Harford (2005) has shown that variations in financial frictions are crucial for capital reallocation through mergers and acquisitions. Reallocation at the disaggregate level, furthermore, has been found to play a key role in explaining U.S. aggregate productivity fluctuations over business cycles (e.g., Basu and Fernald, 2001). Taken together, these observations indicate that variations in financial frictions, by reallocating capital at the disaggregate level, might be important as a transmission mechanism for primitive shocks to translate into aggregate TFP fluctuations.

This paper formalizes the above idea from both theoretical and empirical perspectives. We first construct a model in which financial frictions affect aggregate productive efficiency via capital allocation across different production units (projects). We then introduce news shocks on future technological improvement as a device to identify aggregate TFP fluctuations originating from variations in financial frictions. These shocks are, by construction, uncorrelated to the current production technology, but, at the same time, they affect financial frictions through future profitability. Accordingly, the adoption of news shocks allows us to isolate and identify at firm level variations in credit conditions that are uncorrelated with changes in current technology, a prerequisite to test the roles of financial frictions later in the paper using firm-level data. Our theory shows that endogenous variations of financial frictions in response to such primitive shocks can trigger aggregate TFP fluctuations and business cycles through reallocating capital.

The key ingredient of our model is asymmetric financing constraint across projects. In our

[1] For example, Chari, Kehoe and McGrattan (2007) suggest that fluctuations in aggregate TFP account for most of the post-war business cycle fluctuations. They even claim that a fall in TFP is key in explaining the output decline during the Great Depression. Cole and Ohanian (1999) reach similar conclusions, arguing that a sharp decline in TFP is key to explain the output drop during the Great Depression. Also, Arias, Hansen and Ohanian (2007) claim that a decline in the volatility of TFP can successfully account for the decline in the cyclical volatility of output and its components since 1983.

economy, there are two types of projects: One is subject to a binding financial constraint on the project scale due to limited enforcement of debt payment by entrepreneurs, and the other is not. Given the non-default of the debt contract, debt, and thus, the production scale of a constrained project are limited to a fraction of the future project value for the entrepreneur. The asymmetry of financial constraints implies a gap of marginal product of capital across different types of projects, which creates a potential efficiency gain of reallocating capital from unconstrained to constrained projects.

As a result, any primitive shock that affects the future project value may help to trigger aggregate TFP fluctuations through variations in financial frictions. Candidates for such shocks include news shocks on future technology improvement. Specifically, the arrival of good news causes an immediate jump in the value of the contract by increasing future profitability of the constrained projects. Entrepreneurs, therefore, have less incentive to default on the debt payment. This weakens the financial constraint and induces capital to flow to constrained projects. The efficiency gain arising from capital reallocation shows up in the aggregate economy as an upward shift to current aggregate TFP, and leads to business cycles by allowing positive comovement among current output, consumption, investment, and hours worked.[2]

To evaluate the quantitative implications of our model, we calibrate the economy to the U.S. data. Simulation results indicate that our proposed transmission mechanism of TFP fluctuations can be quantitatively important. In particular, the magnitude of the increase in TFP on impact to a positive news shock, which is purely driven by a reallocation of capital, is about one third of the increase in TFP when technology improvement is materialized. Moreover, business cycle moments of the economy are close to those in the U.S. data. This suggests that our model can replicate the U.S. business cycles reasonably well.

Our theory delivers the following two testable implications regarding our proposed transmission mechanism. First, financial frictions on capital allocations are countercyclical. In other words, we should expect that during an economic expansion (recession), financially constrained firms acquire more (less) capital than unconstrained ones. Second, firm-level variations in expected future profitability affect capital reallocation for financially constrained firms. By contrast, there is no such effect for unconstrained firms. In our model, the first implication provides a channel for financial frictions on capital allocation to affect aggregate TFP at the business cycle frequency, while the second serves as the underlying mechanism for news shocks to affect capital reallocation and, thus, as the micro-foundation for the countercyclicality of

[2] Throughout this paper, we explore the effects of positive news shocks on TFP to illustrate the role of financial frictions as a transmission mechanism. Our proposed mechanism, however, can also be applied to the TFP dynamics during an economic downturn.

frictions on capital allocation.

We use a combined data set from COMPUSTAT and IBES to test the above two implications. We first classify firms into quintiles according to the likelihood of being financial constrained, using the method of Kaplan and Zingales (1997). We find that firms in the bottom quintiles acquire more capital in boom than those in the bottom quintiles do, while the opposite is true for recession. We then use analyst earnings forecast as a proxy for individual firms' prospects for future profitability. Our panel regression shows that the elasticity of capital acquisition to earnings forecast is monotonically increasing in the likelihood of being financial constrained. Our empirical results therefore strongly support both implications of our theory.

Finally, we examine the empirical relevance of a competing channel for business prospects to affect firms' production scale and, thus, business cycles: financial frictions on new capital investment. This channel has been widely adopted in the literature to explain business cycle propagation.[3] We find that the estimated elasticities of investment to earnings forecast are very similar in magnitude across quintiles, suggesting that variations in financial frictions are not likely to be important in investment fluctuations over the business cycles. This, together with our empirical findings for capital acquisition, indicates a more empirically plausible role of financial frictions on capital allocation as a transmission mechanism for aggregate TFP fluctuations.

Our model is closely related to Jermann and Quadrini (2007). They argue that in an economy with financial frictions due to limited enforcement of debt repayment, the mere prospect of high future productivity growth can generate sizable gains in labor productivity through resource reallocation. In their model, however, financial frictions are imposed on the investment of new capital goods. Like other models focusing on frictions distorting saving-investment decisions (referred to as "investment wedge"), variations in such frictions in response to primitive shocks cannot affect productive efficiency on impact. Moreover, a relaxation of the financial constraint induces capital and labor to shift from the consumption good to the investment good sector, implying that consumption and investment comove negatively.[4] In our model, by contrast, relaxing the financial constraint can trigger an immediate expansion of TFP by reallocating existing resources. This makes the positive comovement of macro aggregates feasible.

This paper contributes to the literature on financial frictions. It has long been argued that

[3] See, among others, Kiyotaki and Moore (1997), Bernanke, Gertler, and Gilchrist (1998) and Cooley, Marimon and Quadrini (2004).

[4] The negative correlation between consumption and investment is also present in other existing studies. Beaudry and Portier (2007) have proved that in a two-sector model with constant returns to scale for production, an increase in investment is necessarily associated with a decrease in consumption or hours worked or both. We extended the proof to two-sector models with decreasing returns to scale in one sector or both and financial frictions on the investment good sector (e.g., Kiyotaki and Moore, 1997). The proof is available upon request.

frictions in financial markets are important for business cycles. For example, Bernanke and Gertler (1989), Kiyotaki and Moore (1997) and many other studies show that the presence of financial frictions adds persistence or volatility to aggregate fluctuations over business cycles.[5] More recently, researchers started to pay attention to the role of improving financial markets on Great Moderation (see, for example, Jermann and Quadrini, 2006). Despite this widely accepted view on the importance of financial frictions, their effects through distorting investment have been recently found to play quantitatively minor roles in driving economic fluctuations.[6] Our paper provides a new insight into the role of financial frictions over business cycles. To our knowledge, we are the first to show, both theoretically and empirically, that financial frictions on capital allocation, instead of new capital investment, may serve as a key transmission mechanism for primitive shocks to translate into aggregate TFP fluctuations.

Moreover, our work contributes to the literature on the empirical relationship between resource reallocation and aggregate productivity fluctuations. Basu and Fernald (2000) find that resource reallocation plays a key role in aggregate productivity fluctuations over business cycles. One channel for resource reallocation to affect aggregate productivity is through the countercyclical frictions on capital reallocation. For example, Maksimovic and Philips (2001) find that less productive firms tend to be sold as prospects of the aggregate economy improve. Correspondingly, aggregate output and the productivity dispersion across firms are found to be negatively correlated (Eisfeldt and Rampini, 2006).[7] Harford (2005) provides further evidence that the observed correlation between economic expansion and merger waves is essentially driven by an increase in macro-level capital liquidity and a reduction in the degree of financial frictions correlated with stock market valuation. Consistent with Harford's findings, our empirical results may shed light on the countercyclicality of frictions on capital reallocation: A brighter prospect in booms allows financially constrained firms to acquire more capital than unconstrained firms, thus helping to reduce the gap of marginal product of capital across firms.

This paper is related to the literature on credit or liquidity shocks. These shocks are often adopted as primitive shocks in theoretical work (e.g., Jermann and Quadrini, 2006 and Aghion, Angeletos, Banerjee and Manova, 2007). In our theory, the effects of news shocks on aggregate TFP is observationally very similar to those of credit shocks. Empirically, however, the identification of these two types of shocks involves very different procedures: in our paper,

[5] See Bernanke, Gertler and Gilchrist (1999) for an excellent review of this literature.

[6] For example, business cycle accounting by Chari et al. (2007) suggests that frictions that show up as the investment wedge play, at best, a tertiary role in the Great Depression and the 1982 recession.

[7] Eisfeldt and Rampini (2006) found that the correlation of productivity dispersion with output is around -0.4. This negative correlation is robust to adjustment of capital utilization. Consistent with the empirical finding, the financial friction in our model implies countercyclical productivity dispersion.

news shocks are proxied by individual firms' earnings forecasts. On the other hand, Gilchrist, Yankov and Zakrajsek (2009) approximate credit shocks with credit spreads constructed from yields on long-term senior unsecured bonds. They find that bond spreads contain substantial predictive power of future economic activities over business cycle frequencies. One interpretation of this result, as our model implies, is that a shock to credit markets may reflect news regarding future profitability.

Our paper also contributes to the recent discussion on the role of news shocks in triggering business cycles. On the empirical ground, the VAR estimation of Beaudry and Portier (2006) reveals an almost perfect colinearity between innovations in the growth rate of TFP and innovations in the stock prices index, indicating that innovations in future technological opportunities are largely anticipated.[8] More recently, using structural Bayesian estimation, Schmitt-Grohé and Uribe (2008) find that news shocks to the permanent and stationary components of TFP jointly explain more than two thirds of the variance of output growth over business cycle frequencies. The mechanism for news shocks to drive business cycles, however, is puzzling from the perspective of standard business cycle models, in which mere changes in expectation about future productivity are difficult to generate comovement among consumption, investment and hours worked.[9] This is because, without current changes in TFP, consumption and investment will always comove negatively if they replace one to one with each other. One potential source of the observed TFP changes in response to news shocks is variations in capital utilization.[10] However, in the standard setup with convex investment adjustment costs, an investment boom must be associated with an increase in marginal q, which actually implies a decline in capital utilization. Using "flow" investment adjustment costs, therefore, becomes the key for capital utilization to increase in a boom period (see Jaimovich and Rebelo, 2009). By contrast, both of our theoretical and empirical work shows explicitly how news shocks are transmitted through financial frictions at the disaggregate level into aggregate TFP fluctuations, suggesting that variations in financial frictions can be considered as a potential transmission mechanism for news shocks to drive business cycles.

Finally, this paper is related to a growing literature studying the role of particular fric-

[8] In Beaudry and Portier (2006), news shocks are identified by assusming that they are orthogonal to current TFP. In other words, the anticipation of future productivity growth does not affect current productivity. In our model, however, the arrival of news shocks triggers capital reallocation and, therefore, aggregate TFP fluctuations on impact.

[9] See, for example, Beaudry and Portier (2004), Danthine and Donaldson and Johnsen (1998) and Christiano, Motto and Rostagno (2006).

[10] Den Haan and Kaltenbrunner (2009) explore another potential source of TFP fluctuations: labor hoarding. In their paper, however, the initial responses of consumption and investment move in opposite directions, although labor hoarding may translate into additional resources for economic expansion when there are matching frictions in labor market.

tions on resource allocation and TFP (e.g., Hsieh and Klenow, 2009; Restuccia and Rogerson, 2008; Guner, Ventura, and Xu, 2008; Erosa and Hidalgo Cabrillana, 2007 and Barseghyan and DiCecio, 2005). Much of the literature emphasizes the role of frictions in the cross-country difference of long-run TFP and, therefore, abstracts from the dynamics of such frictions. Recently, Buera and Shin (2008) show the persistent effect of financial frictions on economic development via resource allocation. Our paper instead explores its role for TFP fluctuations over business cycles.

The paper is organized as follows. In Section 2, we illustrate, in a simple model without labor, that financial frictions on capital allocation may act as a transmission mechanism of TFP fluctuations. We then extend the economy to incorporate more features of business cycles in Section 3. Section 4 calibrates the benchmark economy. In Section 5, we report the impulse responses, business cycle statistics and robustness check result. Using firm-level data, Section 6 tests the two implications of our theory. Section 7 concludes. The appendix contains the definition for recursive competitive equilibrium and the derivation of the enforcement constraint.

2 A model without labor

In this section, we describe a model that abstracts from labor as input into production (referred to as "economy without labor") to highlight the role of financial frictions on capital allocation as a transmission mechanism of aggregate TFP fluctuations. A full-blown model with richer business cycle ingredients will be provided in the following section.

Consider an economy with a representative household and a continuum of entrepreneurs with unit mass. The representative household owns physical capital and makes investment decision in physical capital. Entrepreneurs have access to the technology of operating projects. Each entrepreneur can operate only one project.

Projects are classified into two categories, according to whether working capital (or liquid fund) is needed for production. Specifically, a fraction η of projects, denoted as type-h projects, require working capital before production takes place. We assume that the size of the working capital required, denoted as $D\left(k_t^h\right)$, increases with the size of the capital deployed in a type-h project, denoted as k_t^h. For the remaining $1-\eta$ fraction of projects, referred to as type-l projects, working capital is not necessary.

Entrepreneurs are risk-neutral and have no access to savings. Accordingly, each period they decide how much capital to rent from the representative household for profit maximization.

Entrepreneurs retain the ability to operate the project with probability ϕ.[11] Once she loses this ability, the entrepreneur exits the market with no cost, and there will be a new entrepreneur entering the market and starting with the same type of project as her predecessor. This assumption, together with the law of large numbers, enables the fraction of each type of projects to be constant over time.

2.1 Project Financing and the Entrepreneur's Problem

Type-h projects are financed through optimal contracts with limited enforceability à la Jermann and Quadrini (2006). To finance working capital, entrepreneurs of type-h projects borrow from an outside lender at the beginning of each period and repay the debt at the end of the period, after all transactions are completed. As an intra-period loan, it has a zero net interest payment. The ability to borrow, however, is bounded by the limited enforcement of the debt repayment. At the end of the period, the entrepreneur has the ability to divert working capital. Once the entrepreneur defaults, the lender can take over the control right of the project from the entrepreneur and recover a fraction φ (< 1) of the future project value. The entrepreneur and the lender can then renegotiate repayment of the debt. Appendix 8.1 describes the renegotiation process in detail and shows that the incentive-compatibility condition imposes the following financial constraint

$$D\left(k_t^h\right) \leq \theta V_{t+1}^h = \theta E_t \sum_{j=1}^{\infty} \hat{\beta}^j \pi_{t+j}^h, \tag{1}$$

where V_{t+1}^h is the value of a type-h project to the entrepreneur at the end of period t. $\hat{\beta} \equiv \beta\phi$ is the effective discount factor and β is the subjective discount factor. π_{t+j}^h is the one-period profit of a type-h project at period $t + j$. (1) implies that the entrepreneur can borrow up to the amount that he can pledge to the lender, which is a fraction θ of the future project value.[12]

The production technology of a type-i, $i \in \{h, l\}$, is given by

$$y_t^i = Z_t \left(k_t^i\right)^\alpha \tag{2}$$

where k_t^i is capital in a single type-i project. Z_t is the aggregate technology, which follows a stochastic process, as will be described later. We assume $\alpha < 1$. The concavity of production function implies that revenue function displays decreasing returns to scale. The decreasing returns to scale could be rationalized by assuming limited managerial resources as in Lucas

[11] The assumption $\phi < 1$ serves to make sure the boundedness of the future project value, computed as the discounted sums of future profits, in our benchmark model.

[12] Appendix 8.1 shows that θ is positively related to the bargaining power of the lender and the fraction of project value that is recoverable by the lender.

(1978). Alternatively, we could assume that these properties derive from the monopolistic nature of the competitive environment where the entrepreneur faces a downward sloping demand function, as our benchmark model does.

At each period, the entrepreneur of a type-h project chooses capital k_t^h for profit maximization.

$$\max_{k_t^h} c_t^h \equiv Z_t \left(k_t^h\right)^\alpha - \left(r_t + \delta\right) k_t^h, \tag{3}$$

subject to (1). It should be noted that the entrepreneur's problem can be alternatively specified as maximizing the present discounted project profit subject to the sequence of financial constraints (1), by choosing the whole path of capital. The assumption of the rental market for capital, however, makes the choice of capital at each period independent of previous choices. Therefore, the dynamic problem boils down to the sequence of one-period profit-maximization problems, as stated in (3).

The problem of an entrepreneur of a type-l project is

$$\max_{K_t^l} c_t^l \equiv Z_t \left(k_t^l\right)^\alpha - \left(r_t + \delta\right) k_t^l. \tag{4}$$

The first-order condition delivers the standard demand equation of capital

$$k_t^l = \left(\frac{\alpha Z_t}{r_t + \delta}\right)^{\frac{1}{1-\alpha}}.$$

In this simple model, the degree of frictions on capital allocation can be measured as the gap of marginal product to capital ("MPK" henceforth) between two types of projects.

$$\frac{MPK_t^h}{MPK_t^l} = \left(\frac{k_t^h}{k_t^l}\right)^{\alpha-1} \tag{5}$$

Tightening (or relaxing) the financial constraint on type$-h$ projects leads to an increase (or decrease) in the gap of MPK and, therefore, frictions on capital allocation.

A more general but reduced-form approach to modeling frictions on reallocating capital is to assume a quadratic cost of reallocating capital. To obtain countercyclicality of such frictions as observed, one might assume that the magnitude of the adjustment cost parameter is negatively correlated with future profitability (see Eisfeldt and Rampini, 2006). Our model can be seen as providing a micro-foundation for frictions on reallocation capital and its countercyclicality, which will be shown below.

2.2 Aggregate TFP and Primitive Shocks

In standard Real Business Cycle ("RBC" henceforth) models, current technological shocks, by construction, are the only source for aggregate TFP fluctuations. Instead, our purpose here is to show that financial frictions, by distorting capital allocation, serve as a source of aggregate TFP fluctuations. To this end, we decompose the aggregate TFP and its fluctuations to shed light on their potential sources in our economy.

We measure the aggregate TFP as the "Solow Residual." In our economy, aggregate output can be expressed as

$$\begin{aligned} Y_t &= \eta Z_t \left(k_t^h\right)^\alpha + (1-\eta) Z_t \left(k_t^l\right)^\alpha \\ &= TFP_t K_t^\alpha \end{aligned}$$

where

$$TFP_t = \frac{\eta Z_t \left(k_t^h\right)^\alpha + (1-\eta) Z_t \left(k_t^l\right)^\alpha}{K_t^\alpha}$$

Accordingly, the percentage deviation of aggregate TFP from its steady-state value can be expressed as

$$\triangle \log TFP_t = \triangle \log \left(\eta Z_t \left(\frac{k_t^h}{K_t}\right)^\alpha + (1-\eta) Z_t \left(\frac{k_t^l}{K_t}\right)^\alpha\right) \tag{6}$$

Note that the right-hand-side ("RHS" henceforth) of (6) can be further decomposed as

$$\begin{aligned} & \triangle \log \left(\eta Z_t \left(\frac{k_t^h}{K_t}\right)^\alpha + (1-\eta) Z_t \left(\frac{k_t^l}{K_t}\right)^\alpha\right) \\ = & \underbrace{\triangle \log Z_t}_{\text{the technological effect}} + \underbrace{\triangle \log \left(\eta \left(\frac{k_t^h}{K_t}\right)^\alpha + (1-\eta) \left(\frac{k_t^l}{K_t}\right)^\alpha\right)}_{\text{the reallocation effect}} \\ & + \text{cross product terms} \end{aligned} \tag{7}$$

Steady-state values are marked by upper bars. The first argument on the RHS of (7), called "the technological effect," captures the effect of exogenous technological shifts on the aggregate TFP, given the distribution of capital as in the steady state. The second argument, referred to as "the reallocation effect," captures the effect of changes in the distribution of capital across different types of projects, given the technology as in the steady state. In this simple economy, the first-best allocation involves an equal amount of capital allocated across projects. Introducing financial frictions may lead to inefficient capital allocation and, hence, reduce aggregate productive efficiency.

Our purpose is to isolate TFP fluctuations caused by the reallocation effect, which in our model originates from the presence of financial frictions. To this end, we would like to introduce primitive shocks that help to trigger capital reallocation, but bear no contemporaneous technological effect. Note that in our model, any primitive shock affecting future profitability of the constrained projects may help to trigger a reallocation of capital by changing the future project value. One candidate for such shocks is a news shock on future technological change. Specifically, we assume that the aggregate technology Z_t follows

$$\log Z_{t+1} = (1-\rho)\log \bar{Z} + \rho \log Z_t + \epsilon_t^Z, \tag{8}$$

where ϵ_t^Z denotes innovations regarding information on the next-period aggregate technology Z_{t+1}. The process (8) is different from the stochastic technology process in standard RBC models: Information on Z_{t+1} arrives at time t, before Z_{t+1} is realized. As a result, next-period aggregate technology becomes perfectly predictable. Note that the news shock ϵ_t^Z is orthogonal to the current technology Z_t and, hence, cannot affect the aggregate TFP on impact via the technological effect. Instead, such a news shock leads to variations in financial frictions by changing the value of a type-h project, as it contains information about future technology. The revaluation of financially constrained projects triggers a reallocation of capital. Consequently, the reallocation effect is the only source of TFP fluctuations before actual technology shift is realized.

2.3 Household

The representative household solves the following problem

$$\max_{\{C_t, K_{t+1}\}_{t=0}^{\infty}} E_0 \left[\sum_{t=0}^{\infty} \beta^t \frac{C_t^{1-\sigma} - 1}{1-\sigma} \right],$$

subject to

$$C_t + K_{t+1} - (1-\delta) K_t = r_t K_t.$$

We thus obtain the standard Euler equation.

$$C_t^{-\sigma} = \beta E_t \left[C_{t+1}^{-\sigma} (1 + r_{t+1}) \right].$$

2.4 Timing and Information

The events within each period proceed as follows. At the beginning of each period, the previous-period news on the current-period technology is materialized. Meanwhile, news regarding future technological opportunity arrives. Then, the stand-in household supplies capital to entrepreneurs. After production takes place, the household receives factor payments and makes consumption-investment choices. Finally, uncertainty about entrepreneurial survival is revealed.

A formal definition of the competitive equilibrium in a more general model is provided in the next section. The numerical strategy to solve for the equilibrium allocation adopts the standard recursive method.

2.5 Impulse Response to News on Z_t

To illustrate the role of financial frictions as a transmission mechanism of TFP fluctuations, we explore the impulse responses of various macro aggregates to news shocks as a numerical example. We parameterize the working capital requirement, $D\left(k_t^h\right)$ as follows:

$$D\left(k_t^h\right) = \left(k_t^h\right)^{\alpha} \tag{9}$$

Table 1 reports the values of parameters used in our numerical simulation. A calibration exercise will be conducted in the next section, when we introduce our benchmark model.

Table 1. Parameterized Values for Economy w/o Labor

Symbol	Definition	Value
	Technology	
α	Capital share in production function	0.40
ϕ	Entrepreneurial survival rate	0.90
δ	Depreciation rate for capital	0.10
ρ	Autocorrelation coefficient	0.95
σ_{ϵ}^{Z}	Standard deviation of information innovation	0.013
	Preference	
β	Discount factor in utility function	0.94
σ	Coefficient of relative risk aversion	1
	Market	
θ	Default parameter	0.21
η	Fraction of type-h projects	0.45

We consider the following experiment: At period 0, the economy is at steady state. At the beginning of period 1, all agents receive unanticipated news that the aggregate technology Z will increase by one percent in period 2. At the beginning of period 2, the technology improvement is materialized. Our choice of one period as the lag for technological changes to be realized greatly eases the computation burden to solve for policy functions.[13]

Figure 1 plots the impulse response of financial frictions of allocating capital, measured by the ratio of marginal productivity of capital between two types of projects, as well as the dynamics of aggregate TFP. We see from Panel A that in response to the news shock, the gap of marginal product of capital shrinks and stays below the steady-state level throughout the boom period. This suggests that consistent with the empirical evidence, productivity dispersion in our model are countercyclical. This is because, when good news arrives, capital is reallocated from type-l to type-h projects.

[13] For both the model without labor and our benchmark model described in Section 3, the impulse responses remain qualitatively the same if we assume that the technology improvement is realized at period 3.

[Insert Figure 1]

The efficiency gain on impact shows up as an increase in the aggregate TFP. This is evident from Panel B. Most importantly, the reallocation effect explains all of the increase in the aggregate TFP upon the arrival of the good news, reflecting the fact that, in our experiment, financial frictions on capital allocation are the only channel for triggering aggregate TFP fluctuations. After realization of the technology improvement, the technological effect starts to play a role, and the contribution of the reallocation effect to the aggregate TFP declines gradually.

The increase of aggregate TFP makes the comovement of macro aggregates feasible. Figure 2 plots the impulse responses of macroeconomic variables. Although the contemporaneous technology remains unchanged, the arrival of good news generates an economic expansion immediately: aggregate consumption, investment and output all increase on impact. In other words, our model is capable of generating business cycles by establishing a source of TFP fluctuations.

[Insert Figure 2]

In summary, we show, in a simple model, the role of financial frictions as a transmission mechanism of TFP fluctuations through capital allocation: Endogenous variations of financial frictions in response to good news shocks can trigger a reallocation of capital; the redistribution of capital creates an efficiency gain as an increase of aggregate TFP. The increase in TFP allows macro aggregates to comove positively before the actual technology improvement is realized.

3 The Benchmark Model

The basic model of Section 2 has a number of limitations. By implicitly treating labor as a fixed factor in production, the model implies a time-invariant labor allocation across projects. Prohibiting labor reallocation does not seem reasonable, given the importance of job creation and job destruction for U.S. business cycles. Moreover, the basic model is silent on the impulse response of labor supply and, hence, unable to address the issue of fluctuations in aggregate employment. Finally, the basic model attributes all the dispersion in marginal product to the dispersion in physical productivity, while most evidence on the measured dispersion in productivity reflects dispersion in both physical productivity and prices.

This section extends the basic model to overcome these limitations. There are three major changes. First, financial frictions are imposed on allocation of both capital and labor. Accordingly, labor will be reallocated along with capital following variations in financial frictions.

Second, endogenous labor supply is introduced. Third, we adopt product market differentiation to capture productivity dispersion. In addition, we incorporate the following ingredients: trend growth in technology and population; and heterogeneity in productive efficiency across different types of projects. We show that the key mechanism in Section 2 for TFP fluctuations prevails in this extended model (referred to as the "benchmark model" henceforth), which is then calibrated to U.S. data for quantitative assessment.

3.1 Production and Market Structure

Each entrepreneur $i \in [0,1]$ produces an intermediate good y^i, which is used in the production of final goods Y according to:

$$Y = \left(\int_0^1 \left(y^i\right)^\mu di \right)^{\frac{1}{\mu}}, \ \mu < 1$$

The final good producers behave competitively, and the final goods is used by households for both consumption and investment. We call the production unit of intermediate good i as project i. The intermediate good market is monopolistically competitive. Accordingly, the inverse demand function faced by the entrepreneur of intermediate good i is

$$p_i = \left(\frac{Y}{y^i} \right)^{1-\mu} \tag{10}$$

where p_i is the price in units of the final good and $1/\left(1-\mu\right)$ is the elasticity of substitution across projects.

The intermediate good is produced with the input of capital and labor according to Cobb-Douglas technology

$$y_t^i = \left(A_t^i\right)^{\frac{1}{\mu}} \left(k_t^i\right)^\alpha \left(h_t^i\right)^{1-\alpha}, \tag{11}$$

where k_t^i and h_t^i are capital and labor employed in a single project i. (11) allows technology A_t^i to be different across projects. Specifically, A_t^i contains three components.

$$A_t^i = (1+g)^t \chi_t^i Z_t. \tag{12}$$

The first part, $(1+g)^t$, captures the trend of aggregate technology, where g is the long-run growth rate of aggregate technology. The second and the third parts, χ_t^i and Z_t, respectively, refer to the project-specific technology and detrended aggregate technology.

As in the model without labor, projects are classified into two types: type-h projects, constituting a fraction η of all projects, which require working capital to be operative; and type-l projects, for which working capital is not necessary. Without loss of generality, we assume that a project $i \in [0, \eta]$ belongs to type-h projects, while a project $i \in (\eta, 1]$ belongs to type-l projects.

We assume again that the magnitude of working capital for a type-h project to be operative increases in the scale of production. Entrepreneurs of type-h projects face the same limited enforcement problem of debt repayment as those in the model without labor. Similar to the model without labor, the incentive-compatibility condition imposes the following financial constraint

$$D\left(k_t^h, h_t^h\right) \leq \theta V_{t+1}^h = \theta E_t \sum_{j=1}^{\infty} \hat{\beta}^j \pi_{t+j}^h, \tag{13}$$

where $D\left(k_t^h, h_t^h\right)$ stands for the divertible resource.

At each period, the entrepreneur of a type-h project (i.e., $i \in [0, \eta]$) chooses capital k_t^i and labor h_t^i for profit maximization

$$\max_{\left\{k_t^i, h_t^i\right\}} c_t^i \equiv p_t^i y_t^i - (r_t + \delta) k_t^i - w_t h_t^i,$$

subject to (10), (11) and (13). After substituting the demand and production functions, we obtain the revenue function

$$p_t^i y_t^i = Y_t^{1-\mu} A_t^i \left(\left(k_t^i\right)^{\alpha} \left(h_t^i\right)^{1-\alpha}\right)^{\mu}$$

Note that in this model, the curvature in the revenue function originates from the downward sloping demand functions, due to our assumption of product market differentiation ($\mu < 1$).

The problem of an entrepreneur of the type-l project (i.e. $i \in (\eta, 1]$) is

$$\max_{\left\{k^i, h_t^i\right\}} c_t^i \equiv p_t^i y_t^i - (r_t + \delta) k_t^i - w_t h_t^i$$

subject to (10) and (11).

In our baseline case, we assume that only the aggregate technology is stochastic, while the project-specific technology is constant. For simplicity, we assume that production technology is homogeneous for any project $i \in [0, \eta]$.

$$A_t^i = (1+g)^t \chi^h Z_t.$$

Similarly, for any project $i \in (\eta, 1]$, $A_t^i = (1+g)^t \chi^l Z_t$, with $\chi^l \neq \chi^h$. As a result, in equilibrium, we have $k_t^i = k_t^h$ and $h_t^i = h_t^h$ ($k_t^i = k_t^l$, and $h_t^i = h_t^l$) for all entrepreneurs $i \in [0, \eta]$ ($i \in (\eta, 1]$). Without loss of generality, we thus denote variables $x^i = x^h$ (x^l) for $i \in [0, \eta]$ ($i \in [\eta, 1]$). In Appendix 8.3, we explore the model predictions when project-specific technology is stochastic.

The first-order conditions of the two types of entrepreneurs' problem imply the following allocation of capital between two types of projects.

$$\begin{aligned}
& \alpha\mu Y_t^{1-\mu} A_t^h \left(k_t^h\right)^{\alpha\mu-1} \left(h_t^h\right)^{(1-\alpha)\mu} - \lambda_t^h D_{k_t^h} \\
= \;& \alpha\mu Y_t^{1-\mu} A_t^l \left(k_t^l\right)^{\alpha\mu-1} \left(h_t^l\right)^{(1-\alpha)\mu} \\
= \;& r_t + \delta \qquad (14)
\end{aligned}$$

where λ_t^h is the Lagrangian multiplier associated with the financial constraint (13). D_x denotes the partial derivative of D to variable x. Similarly, the allocation of labor follows

$$\begin{aligned}
& (1-\alpha)\,\mu Y_t^{1-\mu} A_t^h \left(k_t^h\right)^{\alpha\mu} \left(h_t^h\right)^{(1-\alpha)\mu-1} - \lambda_t^h D_{h_t^h} \\
= \;& (1-\alpha)\,\mu Y_t^{1-\mu} A_t^l \left(k_t^l\right)^{\alpha\mu} \left(h_t^l\right)^{(1-\alpha)\mu-1} \\
= \;& w_t \qquad (15)
\end{aligned}$$

Two remarks are in order. First, in the first-best allocation where the financial constraint is not binding ($\lambda_t^h = 0$), both types of projects have the same capital-labor ratio.

$$\frac{k_t^h}{h_t^h} = \frac{k_t^l}{h_t^l} = \frac{\alpha w_t}{(1-\alpha)(r_t+\delta)}. \qquad (16)$$

Moreover, the first-best allocation of capital is determined by the relative production technology.

$$\frac{k_t^h}{k_t^l} = \left(\frac{A_t^h}{A_t^l}\right)^{\frac{1}{1-\mu}}. \qquad (17)$$

Second, comparing the first-order condition in (14), it is immediate that news on an individual type-h project's future technology A_{t+j}^h can affect k_t^h by changing the tightness of financial constraint in (13) and, therefore, λ_t^h. By contrast, news about A_{t+j}^l has no direct impacts on k_t^l.[14] We will use firm-level data to test this implication in Section 6.

Finally, we parameterize the divertible resource as

$$D\left(k_t^h, h_t^h\right) = \Omega_t \left(k_t^h\right)^{\alpha} \left(h_t^h\right)^{1-\alpha}. \qquad (18)$$

where $\Omega_t = (1+g)^{\frac{t}{\mu}}$ is multiplied to ensure the long-run growth rate of the required working capital is the same as that for profits, so that financial constraints are always binding on the balanced growth path. (18) is a natural extension of the specification (9). It is easy to show

[14] In our model, news about A_{t+j}^l can affect K_t^l indirectly via the general equilibrium effect since type-l projects are homogeneous. The general equilibrium effect disappears if we consider A_{t+j}^l as an idiosyncratic shock.

that (18) gives rise to the following property: Both types of projects have the same capital-labor ratio, a feature of the first-best allocation. The equality of the capital-labor ratio across projects shuts down the within-project resource misallocation (between capital and labor) as a potential source for efficiency gain and allows us to focus on the effect of resource reallocation *across* projects on aggregate productive efficiency.

Following Foster, Haltiwanger and Syverson (2008) and Hsieh and Klenow (2009), we distinguish between "physical productivity", denoted as $TFPQ$, and "revenue productivity", denoted as $TFPR$. Specifically

$$\begin{aligned} TFPQ^i &= \frac{y^i}{(k^i)^\alpha (h^i)^{1-\alpha}} = \left(A^i\right)^{\frac{1}{\mu}} \\ TFPR^i &= \frac{p^i y^i}{(k^i)^\alpha (h^i)^{1-\alpha}} = p^i \left(A^i\right)^{\frac{1}{\mu}} \end{aligned}$$

for $i = h, l$. Note that even in the first-best case, $TFPQ$ are different between the two types of projects due to the heterogeneity in project-specific technology. However, unlike $TFPQ$, $TFPR$ will be the same across projects if there is no financial friction. This is because more capital and labor should be allocated to projects with high $TFPQ$ to the point where their higher output results in a lower price and thus the exact same $TFPR$. The presence of financial frictions drives a dispersion of $TFPR$ across different types of projects. This allows us to use the ratio of $TFPR$ as our measure of financial frictions on capital allocation.

$$\begin{aligned} \frac{TFPR^h}{TFPR^l} &= \frac{p^h}{p^l}\left(\frac{A^h}{A^l}\right)^{\frac{1}{\mu}} \\ &= \frac{A^h}{A^l}\left(\frac{k^h}{k^l}\right)^{\mu-1} \end{aligned} \tag{19}$$

where the second equality of (19) derives from our model property that the capital-labor ratio is the same across projects. Under this model property, the ratio of $TFPR$ is equal to the ratio of marginal revenue product of capital, defined as $MRPK^i = \frac{\partial p^i y^i}{\partial k^i}$. Clearly, the presence of financial frictions constrains k^h relative to k^l and drive the ratio of $TFPR$ above one. Note that a larger degree of product differentiation (smaller μ) tends to drive up the ratio of $TFPR$ and, thus, amplify the distortion of financial frictions on aggregate TFP.

3.2 A Decomposition of TFP

We then decompose the aggregate TFP as

$$\begin{aligned} \log TFP_t &= \log \frac{Y_t}{K_t^\alpha H_t^{1-\alpha}} \\ &= \frac{1}{\mu}\log\left(\eta A_t^h \left(\frac{k_t^h}{K_t}\right)^\mu + (1-\eta) A_t^l \left(\frac{k_t^l}{K_t}\right)^\mu\right) \end{aligned} \tag{20}$$

where the second equality in (20) is derived from the feature that the capital-labor ratios across different types of projects are equal in our model. The percentage deviation of aggregate TFP from its balanced growth path can be decomposed as

$$\begin{aligned}
\triangle \log TFP &= \underbrace{\frac{1}{\mu}\triangle \log\left(\eta A_t^h\left(\frac{k_t^h}{K_t}\right)^{\mu}+(1-\eta)\,A_t^l\left(\frac{k_t^l}{K_t}\right)^{\mu}\right)|_{\frac{k_t^i}{K_t}=\overline{\frac{k^i}{K}}}}_{\text{the technological effect}} \\
&\quad +\underbrace{\frac{1}{\mu}\triangle \log\left(\eta A_t^h\left(\frac{k_t^h}{K_t}\right)^{\mu}+(1-\eta)\,A_t^l\left(\frac{k_t^l}{K_t}\right)^{\mu}\right)|_{A_t^i=\overline{A}^i}}_{\text{the reallocation effect}} \\
&\quad +\text{cross product term.} \qquad (21)
\end{aligned}$$

The first and second arguments on the RHS of (21) are the "technological effect" and the "reallocation effect," which bear meanings similar to those of their counterparts in the economy without labor. To understand further the reallocation effect, we express aggregate TFP as

$$TFP_t = \frac{1}{\left[\eta\left(\frac{A_t^h}{TFPR_t^h}\right)^{\frac{1}{1-\mu}}+(1-\eta)\left(\frac{A_t^l}{TFPR_t^l}\right)^{\frac{1}{1-\mu}}\right]} \qquad (22)$$

Note that $\left(\frac{A_t^i}{TFPR_t^i}\right)^{\frac{1}{1-\mu}}$ is strictly convex in $TFPR$. Equation (22) shows that the larger is the spread between $TFPR_t^h$ and $TFPR_t^l$, the smaller is the level of TFP_t. Therefore, capital reallocation causes aggregate TFP to fluctuate through the dispersion of $TFPR$ across different types of projects.

Our model assumes fixed share of different types of projects to highlight the role of financial frictions on capital reallocation among incumbent producers. Accumulating evidence, on the other hand, suggests that entry/exit margins play a critical role in the contribution of reallocation to productivity growth as well as to the dispersion of productivity and profitability across businesses. Since startups and young businesses are particularly vulnerable to financial frictions, variations in financial frictions are potentially key to understanding entry/exit over the business cycles and their contribution to the cyclical variations in the dispersion of profitability across businesses. We leave it as an important topic for future research to investigate the role of financial frictions on aggregate productivity fluctuations through endogenous entry and exit.[15]

[15] In an appendix upon request, we construct a model with endogenous entry, where entry cost takes the form of a fixed amount of labor. We find that in this model the countercyclicality of financial frictions over business cycles leads to procyclical entry of type-h projects. This channel both amplifies and propagates TFP fluctuations over business cycles.

Finally, in order to highlight the reallocation effect, we again specify primitive shocks as news shocks on future aggregate technology as in (8). Changes in aggregate TFP, therefore, are driven purely by the reallocation effect before the technology change is materialized.

3.3 Household Sector

For calibration, we incorporate trend growth in population into the household problem. There is a stand-in household with N_t working-age members at date t. The size of the household evolves over time exogenously at a constant rate $n = N_t/N_{t-1} - 1$. In this framework, the representative household's problem solves

$$\max_{\{c_t, h_t, k_{t+1}\}_{t=0}^{\infty}} E_0 \left[\sum_{t=0}^{\infty} \beta^t N_t u\left(c_t, h_t\right) \right],$$

subject to

$$\begin{aligned} C_t + I_t &= r_t K_t + w_t H_t, \\ K_{t+1} &= \left(1-\delta\right) K_t + I_t \end{aligned}$$

where $c_t \equiv C_t/N_t$ is per member consumption, $h_t \equiv H_t/N_t$ is the fraction of hours worked per member of the household. We abstract from investment adjustment cost to highlight financial frictions on capital allocation as the key mechanism of the model.[16] g_y is the growth rate of output per capita at the balanced growth path, which follows

$$1 + g_y = \left(1+g\right)^{\frac{1}{(1-\alpha)\mu}}.$$

The first-order conditions imply the following standard equations

$$\begin{aligned} u_c\left(c_t, h_t\right) w_t &= -u_h\left(c_t, h_t\right), \\ u_c\left(c_t, h_t\right) &= \beta E_t\left[u_c\left(c_{t+1}, h_{t+1}\right)\left(r_t + 1 - \delta\right)\right], \end{aligned}$$

where $u_x\left(c_t, h_t\right)$ is the marginal utility (or disutility) associated with variable x, $x = c$ or h.

Finally, we keep the timing and information structures the same as those in the economy without labor.

[16] Cooper and Haltiwanger (2006) find that a model which mixes both convex and non-convex adjustment costs fits best the observed investment behavior at the plant level. Incorporating non-convex adjustment costs can potentially strengthen the importance of capital reallocation for productivity fluctuations over business cycles. Intuitively, the presence of non-convex investment adjustment costs (e.g. disruption costs) tends to encourage capital acquisition, instead of new investment, by financially constrained firms as a short-run response to news about future profitability. Our evidence in Section 6.3 and 6.4 supports this prediction.

3.4 Competitive Equilibrium

A competitive equilibrium of this economy consists of an allocation $\{C_t, H_t, K_{t+1}, I_t, Y_t\}_{t=0}^{\infty}$ for the representative household, allocation $\{c_t^j, k_t^j, h_t^j, p_t^j, y_t^j\}_{t=0, j\in\{h,l\}}^{\infty}$ for entrepreneurs, and price system $\{w_t, r_t\}_{t=0}^{\infty}$ such that

- Given prices, the allocation $\{C_t, H_t, K_{t+1}\}_{t=0}^{\infty}$ solves the household's problem.
- Given $\{w_t, r_t\}$, $\{c_t^j, k_t^j, h_t^j, p_t^j, y_t^j\}_{,j\in\{h,l\}}$ solves the entrepreneur's profit maximization problems.
- Capital market clears: $\eta k_t^h + (1-\eta)\, k_t^l = K_t$.
- Labor market clears: $\eta h_t^h + (1-\eta)\, h_t^l = H_t$.
- p^i is such that the intermediate good market i clears.
- Final good market clears:

$$C_t + \eta c_t^h + (1-\eta)\, c_t^l + I_t = Y_t.$$

  where aggregate consumption, $C_t + \eta c_t^h + (1-\eta)\, c_t^l$, is measured as the sum of the representative household's and entrepreneurial consumption.

We define the recursive competitive equilibrium in Appendix 8.2. For numerical solution, we detrend each per capita variable except hours worked by dividing it by $(1+g_y)^t$. We solve for decision rules by policy function iterations.

4 Calibration

In this section, we calibrate the benchmark model using data from the 2005 revision of National Income and Product Accounts (NIPA) to match the average values of U.S. data over the 1960-2004 period. Our measure of capital stock includes government capital and stock of consumer durables, following Cooley and Prescott (1995). One period in the model corresponds to one calendar year.

4.1 Preference

Two types of utility preference are commonly used in RBC literature. The first is the utility specification in Greenwood, Hercowitz and Hoffman (1988, "GHH" henceforth). Under GHH preference, the income effect on labor supply is shut down, and the only channel for shocks to affect labor supply is the substitution effect of changes in wage rates. King, Plosser and Rebelo (1988) propose a different class of preference ("KPR" henceforth), in which sufficiently large income effects on labor supply are required to keep the stationarity of hours on the balanced growth path. Little evidence has so far existed on the income effects of aggregate labor supply, except for Schmitt-Grohé and Uribe (2008), which find a near zero value under a structural Bayesian estimation. We therefore adopt the GHH preference as the benchmark calibration to keep the simplicity of the model, which allows us to focus on the main mechanism in this paper.

$$u(c_t, h_t) = \frac{\left(c_t - \psi \Gamma_t \frac{h_t^{1+\nu}}{1+\nu}\right)^{1-\sigma} - 1}{1-\sigma}, \tag{23}$$

where $\Gamma_t = (1+g_y)^t$ is incorporated in the utility to ensure the stationarity of hours on the balanced growth path. In Section 5.3.3, we will check the robustness of our results under a generalized preference proposed by Jiamovich and Rebelo (2009), which nests as special cases both GHH and KPR preferences.

We set $\sigma = 1$, which corresponds to the case of logarithmic utility. ν is set to 0.4 to match a Frisch elasticity of 2.5.[17] The parameter ψ is set to 1.58 so that the hours worked is 0.33 at the steady state. The discount factor β is set to 0.979, implying a steady state real interest rate of 4 percent. The population growth rate n is set to 0.0147, which is the average growth rate of the civilian non-institutional population aged 16 over between 1960 and 2004.

Since in our model there are only two types of projects, we set $\eta = 0.45$ to be consistent with the results of Kaplan and Zingales (1997), which found that about 45 percent of the firms in their sample were likely to be financially constrained.[18] We let the entrepreneurial survival probability ϕ be 0.90, which is broadly consistent with the firm survival probability in U.S. data for manufacturing and business service sectors, as reported by OECD (2001).

4.2 Technology

We set $g_y = 0.0183$, which is consistent with the long-run average growth rate of U.S. real GNP per capita. The price markup over the average cost for a type-l project is $1/\mu - 1$. We set $\mu = 0.85$, the value in Atkeson and Kehoe (2005) for the span of control parameter of a plant's manager. This implies a markup of 17.6 percent, consistent with the empirical evidence

[17] A Frisch elasticity of 2.5 reflects both the intensive and extensive margins of aggregate labor supply.

[18] More specifically, Kaplan and Zingales (1997) develop a criterion to classify firms into groups in terms of likelihood of being financially constraint. They find that among a sample of 49 firms, 19 firms are never financially constrained over the entire sample period, 8 firms are possibly financially constrained at some time, and 22 firms are likely financially constrained at some time.

by Morrison (1992).[19] The parameter α is set so that the labor income share is close to 0.6. Because most of the production comes from type-l projects, we use the labor income share for type-l projects, $(1-\alpha)\,\mu$, to calibrate α.[20] This yields a value of $\alpha = 1 - \frac{0.6}{\mu} = 0.294$. The depreciation rate δ is set to match an investment capital ratio of 0.074, the average between 1960 and 2004. This gives $\delta = 0.04$.

For parameters governing the technology process, we set $\rho = 0.95$ to match a quarterly persistence of 0.987. The standard deviation of innovation σ_ϵ^Z is set equal to 1.55 percent such that the standard deviation of the H-P filtered log TFP simulated from the model is equal to the corresponding value from annual U.S. data.

We normalize the type-l project-specific technology χ^l to 1. Since both the capital-output ratio and the productivity dispersion between the two types of projects are closely related to χ^h and θ, we can calibrate the values of χ^h and θ simultaneously to match two targets: an aggregate capital-output ratio of 2.5 and an empirical ratio of $TFPR$ between the 25th and the 75th percentile producers. According to Table 1 in Syverson (2004), the ratio of TFP between the 25th-percentile producers to the 75th-percentile producers is 1.56. Accordingly, $\chi^h = 1.55$ and $\theta = 0.134$.[21] Our sensitivity analysis in Section 5.3.1 shows that the following quantitative results are essentially unchanged with $\eta = 0.25$, and χ^h and θ recalibrated to match the same moments.

Finally, it should be noted that in addition to financial frictions, many alternative frictions might contribute to the observed TFP dispersion across plants.[22] The observed dispersion in $TFPR$ can thus be viewed as the upper bound of the TFP dispersion caused by financial frictions.[23] Our evidence in Section 6.2, nevertheless, points to financial frictions as a key friction in capital reallocation over the business cycles. Hence, we view financial frictions a potentially important factor underlying the observed TFP dispersion through misallocating

[19] Morrison (1992) provides estimates for markups in the U.S. manufacturing sector for the period 1960-1981 and finds an average markup of 17 percent over marginal cost.

[20] The labor income share for type-h projects is lower than $(1-\alpha)\,\mu$. This is because in the benchmark model, the financial constraints are imposed on both capital and labor. Accordingly, the presence of financial constraints causes the marginal revenue product of labor, denoted as $\frac{\partial p^h y^h}{h^h}$, to be higher than the wage rate.

[21] A higher expected level of technology for type-h projects is consistent with the empirical findings. For instance, Carpenter and Petersen (2002) find that many small high-tech firms in the COMPUSTAT database obtain little debt financing. Accordingly, Opler, Pinkowitz, Stulz and Williamson (1999) find that firms with stronger growth opportunities and higher R&D expenses, as measured by a high market to book ratio and R&D to sales ratio, have larger cash holdings, suggesting that they are more likely to be credit-constrained.

[22] These frictions include, for examples, labor market regulations, policies on size restriction, trade barriers and government subsidies to public enterprises. Most of the above-mentioned frictions are considered by the literature as sources of resource misallocation in developing countries.

[23] As a robustness check, we recalibrate χ^h and θ to target a lower ratio of $TFPR$ (1.28) and a capital-ouput ratio of 2.5. Our results remain qualitatively the same under this alternative calibration. In particular, the on-impact increase in aggregate TFP is only dampened by less than one third.

capital.

Table 2 summarizes the calibrated parameters.

Table 2. Parameter Values For the Benchmark Economy

Symbol	Definition	Value
	Demographics	
n	Population growth rate	0.015
	Technology	
α	Capital share in production function	0.294
g_y	Growth rate of output per capita	0.018
ϕ	Entrepreneurial survival rate	0.90
δ	Depreciation rate for capital	0.04
χ^h	Expected type-h project-specific technology	1.55
μ	Elasticity parameter	0.85
ρ	Autocorrelation coefficient	0.95
σ_ϵ^Z	Standard deviation of information innovation	0.016
	Preference	
β	Discount factor in utility function	0.979
ψ	Disutility parameter for leisure	1.58
σ	Coefficient of relative risk aversion	1
ν	Inverse of Frisch elasticity	0.4
	Market	
θ	Default parameter	0.134
η	Fraction of high-tech projects	0.45

5 Results

In this section, we first plot impulse responses of macro variables to news shocks on aggregate technology. We then report the business cycle statistics. Finally, we conduct robustness check to alternative model parameterization and specification.

5.1 Impulse Responses to News

The experiment for impulse responses are similar to those in the economy without labor: at period 0, the economy is at the steady state. At the beginning of period 1, all agents receive unanticipated news that Z_t will increase by one percent at period 2. At the beginning of period 2, the technology improvement is materialized.

Figure 3 depicts the responses of various variables to a one-percent news shock. We see from panel A that in response to the news shocks, the gap of $TFPR$ between the two types of projects decreases by more than 0.6 percent and stays below the steady-state level throughout the boom period. Hence, the countercyclical feature of financial frictions on capital allocation still prevails when endogenous labor supply and reallocation are allowed for. Moreover, the gap of $TFPR$ reverts gradually to the steady state, suggesting that variations in financial frictions have persistent effects.

[Insert Figure 3]

The reduction of financial frictions on capital allocation results in an increase in aggregate productive efficiency. This is evident from Panel B, which plot the response of aggregate TFP and its components to the good news. The initial response of TFP amounts to 0.5 percent, which is roughly one third of the magnitude of the TFP increase when technology improvement is realized. The decomposition shows that reallocation effects explain all the increase in TFP before the technology improvement is materialized. In addition, due to their persistence, reallocation effects also serve to amplify TFP fluctuations when technology improvement is realized.

The increase in aggregate TFP on impact leads to comovement of macro aggregates, as can be seen from Panel C to F. Though the exogenous technology improvement materializes at period 2, the economy starts to boom at period 1. Aggregate output, consumption, investment, and hours worked all increase on impact. In particular, the response of labor supply is very persistent under the GHH preference.

5.2 Business Cycle Statistics

We now compare business cycle moments in the U.S. data with those simulated from the calibrated model. To simulate the economy, we first use the quadrature method described in Tauchen and Hussey (1991) to construct a three-state Markov chain that approximates news shock processes (8). We then simulate the economy 500 times, each containing 45 periods, as our data span for 45 years. Then, both artificial and actual U.S. data are H-P filtered with a weight of 100. We use their cyclical components to compute the business cycle statistics for both data series.

Table 4 reports the business cycle statistics of second moments of macro variables. Our model generates a 2.49-percent of the standard deviation of simulated output, larger than the corresponding value in the U.S. data (1.73 percent). By contrast, output data simulated from standard RBC models are less volatile than the U.S. data. This suggests that the presence of financial frictions amplifies business cycle fluctuations, as pointed out by Carlstrom and Fuerst (1997), among many others. The simulated volatilities of other macro variables have the standard ordering: consumption and hours worked are less volatile and investment is more volatile relative to output. Moreover, all macro variables generated by the model are highly procyclical, consistent with the stylized fact of U.S. business cycles. With only one shock, our model, like standard RBC models, tends to overestimate contemporaneous correlation coefficients.

Table 4. Business Cycle Statistics, Benchmark Model and Data

	Data	Benchmark	Noisy News
Used for calibration			
σ_{TFP}	0.0125	0.0125	0.0125
Not used for calibration			
σ_Y	0.0173	0.0249	0.0247
σ_C/σ_Y	0.694	0.827	0.824
σ_I/σ_Y	3.451	1.783	1.791
σ_H/σ_Y	0.890	0.722	0.720
$corr\,(C, Y)$	0.719	0.999	0.999
$corr\,(I, Y)$	0.854	0.997	0.998
$corr\,(H, Y)$	0.934	1.000	1.000

To summarize, the simulation results of our benchmark model indicate that our proposed transmission mechanism of TFP fluctuations can be quantitatively important. Moreover, business cycle moments of the economy are close to those in the U.S. data. This suggests that our model can replicate the U.S. business cycles reasonably well.

5.3 Sensitivity Analysis

In this section, we first check the robustness of our quantitative results to the share of financially constrained firms. We then examine our comovement results under a generalized preference proposed by Jiamovich and Rebelo (2009). Finally, we explore the sensitivity of our business cycle statistics to noisy news.

5.3.1 The Share of Financially Constrained Firms

We examine the robustness of our quantitative results to η, the share of constrained firms. Although the parameterization of η in the benchmark case can be motivated from the empirical study of Kaplan and Zingales (1997), it is worth assessing the extent to which the choice of η may change the results. To this end, we reduce the share of constrained firms by half so that $\eta = 0.25$. Our targets are the same as in our benchmark model: an empirical ratio of labor productivity of 2 between the 25th- and the 75th-percentile producers and an aggregate capital-output ratio of 2.5. Since project-specific technology is homogeneous within each type of entrepreneur in our model, $\eta = 0.25$ can be seen as a lower bound for the fraction of constrained firms in order to match the $TFPR$ ratio between the 25th- and the 75th-percentile producers. Accordingly, $\chi^h = 1.77$ and $\theta = 0.127$.[24]

Figure 4 plots the impulse responses to a one-percent positive news shock on Z. Interestingly, the results are essentially the same as those in Figure 3. The reason for the similarity of impulse responses under different η is as follows. A smaller share of financially constrained firms tends to reduce the total amount of capital reallocated from type-l to type-h projects and, thus, the aggregate efficiency gain from reallocation. On the other hand, it also tends to increase the capital-output ratio at the aggregate level. To maintain the aggregate capital-output ratio, an increase in χ^h is required.[25] A higher χ^h facilitates more capital to be reallocated from type-l to type-h projects and, therefore, tends to increase the aggregate efficiency gains. Our simulation indicates that the negative effect of a small η and the positive effect of a large χ^h on the reallocation effect are quantitatively similar under our calibration strategy and, therefore, create no major changes to our results.

[Insert Figure 4 here]

5.3.2 Jiamovich-Rebelo Preference

The utility specification in our benchmark model (GHH preference) abstracts away the income effect on labor supply. As a result, an increase in aggregate TFP due to a reduction in financial frictions on capital allocations will always lead to positive response of hours worked through the substitution effects. In this section, we check the robustness of the comovement results to alternative preferences with income effects on labor supply. Due to the hump-shape response of aggregate TFP to news shocks, hours worked may potentially fall on impact of news shocks if the income effects are sufficiently large. Our question is therefore how small the income effect should be in order to maintain a positive comovement among the macro variables, in particular hours worked.

To address this question, we adopt the preference proposed Jiamovich and Rebelo (2009)

$$u(c_t, h_t) = \frac{\left(c_t - \psi \frac{h_t^{1+\nu}}{1+\nu} \xi_t\right)^{1-\sigma} - 1}{1-\sigma}, \tag{24}$$

where ξ_t is a geometric average of current and past consumption level, which can be written recursively as

$$\xi_t = c_t^{\gamma} \left(\xi_{t-1} \left(1 + g_y\right)\right)^{1-\gamma}$$

[24] We also recalibrate $\psi = 1.71$ to match hours worker to be 0.33 at the steady state.

[25] Accordingly, a lower θ is needed to maintain the ratio of labor productivity of two types of projects.

We impose $\gamma \in [0,1]$. Note that when $\gamma \to 0$, the argument of the period utility function becomes linear in consumption and a function of hours worked, which is the GHH preference as in our benchmark model. On the other hand, when $\gamma = 1$, we obtain preferences of the class discussed in King Plosser and Rebelo (1988). As γ becomes larger, the income effects on leisure are stronger.

We search for the maximum value of γ to allow positive comovements of macro variables on impact to news shocks to aggregate technology, given our benchmark calibration for all other parameters. We find that as γ increases, the impact response of both hours worked and investment to news shocks fall. The value of γ has to be no larger than 0.72 to obtain the positive comovement of all macro variables. We also check the maximum value for γ when aggregate investment is subject to the standard quadratic adjustment cost calibrated to match the estimated result of Gilchrist and Himmelberg (1995). We find that the maximum value for γ increases to 0.92 when adjustment costs are present. Therefore, although the model does not generate aggregate comovement under KPR preference, short-run income effects on labor supply can still be substantially large to maintain the comovement results.

5.3.3 Noisy News

We have maintained the assumption of "perfect news" throughout the text. Now we extend the model by allowing agents to receive "noisy news." Let S_t stand for the signal available at period t. We assume that S_t follows a standard AR(1) process as in (8):

$$\log S_{t+1} = (1-\rho)\log \bar{S} + \rho \log S_t + \epsilon_t^S. \tag{25}$$

The probability for the signal to be precise is a constant, denoted by $q \equiv \Pr(Z_{t+1} = S_{t+1})$. Note that $q = 1$ when news are perfect. The same quadrature method described above is applied for constructing a three-state Markov chain that approximates (25). Denote $\{S^b, S^n, S^g\}$ the state space. Then, the precision of the signal can be written as

$$\Pr\left(Z_{t+1} = S^i | S_{t+1} = S^i\right) = q,$$

where $i \in \{b, n, g\}$. We further assume that

$$\Pr\left(Z_{t+1} = S^j | S_{t+1} = S^i\right) = \frac{1-q}{2},$$

for $j \neq i$. As a robustness check, we set $q = 0.9$. The standard deviation of the noisy signal is calibrated to match the observed standard deviation of TFP. The calibrated standard deviation is 18% smaller than that in the benchmark case with perfect news, indicating that noisy news can generate more volatile TFP over the business cycle. The third column of Table 4 reports the sample statistics of second moments of macro variables. Compared with the results from the benchmark model with perfect news, consumption becomes slightly less volatile while the volatility of investment increases. The other results are almost identical to those with perfect news. Therefore, the business cycle properties of our model are robust to noisy news.

6 Empirical Evidence

So far, we have constructed a theory in which financial frictions on capital allocation serve as a transmission mechanism of TFP fluctuations. To what extent is our proposed mechanism empirically relevant for aggregate TFP fluctuations? An answer to this question relies on two sub-questions. First, to what extent do resource reallocations contribute to aggregate productivity fluctuations? Given its quantitative importance, the next question is whether primitive shocks can lead to countercyclical variations in financial frictions and, therefore, resource reallocation over the business cycles.

The evidence from Basu and Fernald (2000) provides strong support for the importance of reallocation for aggregate productivity fluctuations over business cycles. Specifically, they decompose aggregate Solow residuals into four components: (i) procyclical technology shock; (ii) widespread imperfect competition and increasing returns; (iii) variable utilization of input over the cycle; and (iv) resource reallocation. The reallocation effect reflects changes in an economy's ability to produce goods and services for final consumption from given primary inputs of capital and labor. Using industry-level data compiled by Dale Jorgenson and Barbara Fraumeni, Basu and Fernald find that when subtracting the estimated reallocation terms from Solow residuals, the correlation between Solow residuals and output fell to about zero. This indicates that reallocation over the business cycle is key to understanding aggregate productivity fluctuations.

Regarding the second question, our theory suggests a role for news shocks to cause variations in financial frictions, which trigger capital reallocation and aggregate TFP fluctuations. The theory delivers two testable implications regarding the transmission mechanism. First, financial frictions on capital allocation are countercyclical. This implies that financially constrained firms acquire more capital in boom than unconstrained firms do, while the opposite is true in recession. Second, prospects on an individual firm's future profitability affect financially constrained firms' capital acquisition, but not unconstrained firms'. This hypothesis, together with the procyclicality of forecast on individual firms' future profitability, provides a microfoundation for financial frictions on capital allocation to be countercyclical. The rest of the section aims to test both implications using firm-level data.

6.1 Data

One of the major difficulties of the test is how to distinguish firms that are financially constrained from those that are not. We use an index constructed by Lamont, Polk and Saa-Requejo (2001), which is based on Kaplan and Zingales (1997), to measure the likelihood of a firm being financial constrained. We denote the index as KZ.

KZ is a weighted average of a firm-year's cash flow, cash dividends, cash balances, leverage and firm's average Q, with negative weights on the first three and positive ones on the last two. These weights are obtained by estimation of ordered logit models of the probability that a firm falls in one of the five categories: (1) not financially constrained; (2) likely not to be financially constrained; (3) difficult to classify as either constrained or not; (4) likely to be financially constrained; (5) undoubtedly to be financially constrained.[26] A higher KZ, therefore, implies a higher possibility of being financially constrained. The KZ index has been adapted in some recent empirical work by Lamont, Polk and Saa-Requejo (2001) and Baker, Stein and Wurgler (2003). In particular, Baker et al. (2003) found that the investment of firms with larger KZ is more sensitive in response of Q. We will borrow the empirical strategy of Baker et al. (2003), with a focus on the impact of profitability forecasts on acquisition (rather than the impact of Q on investment).

Forecast data are obtained from the IBES database. IBES asks analysts to provide forecasts of earnings for each firm in the database. Three variables are available: one- and two-year-ahead forecasts for earnings per share, and the long-term growth forecast (LTG) representing an expected annual growth in earnings over the next business cycle (a period over the next three to five years). When calculating their forecasts of long-term growth, IBES instructs analysts to ignore the *current state* of the business cycle and to project, instead, the expected trend growth of the company's earnings. Thus, by the instruction of IBES, the long-term growth forecasts should contain information not in the one-year-ahead and two-year-ahead forecasts, which necessarily will be affected by current conditions.[27] Instead, it should capture information on variables that affect firms' profitability over the next business cycle. This objective is exactly in line with our definition of "news shocks." Therefore, we use long-term

[26] See Kaplan and Zingales (1997) for details on how to classify the firm-years into these five categories based on both objective and subjective criteria. Since firm's average Q is closely related to expected future profits, we use a four-variable version of the index that omits average Q (see, also, Baker, Stein and Wurgler, 2003). Using the original index does not change our main results.

[27] See also Cummins et al. (2006, pp. 799) for a detailed description of the construction of long-term growth forecasts by IBES.

growth forecast as a proxy for "news" in our model. We use the mean of LTG across analysts.[28] Later, we will check the robustness of our empirical results to the potential impacts of current earnings profitability on LTG.

Firm-level data on capital reallocation and variables used to construct the KZ index are from COMPUSTAT.[29] COMPUSTAT data distinguish between expenditure on new capital investment (Item 128) and expenditure on existing capital. Deploying existing capital can take two approaches: transfer of ownership of capital (acquisition and plant/equipment sales) and capital lease. Leasing is especially relevant for small firms, which are found to be more vulnerable to financial constraints.[30] COMPUSTAT provides information on rental expenses, which include operating lease expenses in addition to other payments associated with the lease. However, measuring operating expenses for leasing existing capital is difficult. Therefore, our measurement of the size of capital reallocation (CR) for each individual firm includes only acquisitions (COMPUSTAT Annual Item 129) minus sales of property, plant and equipment (Item 107), though we fully realize that inclusion of leasing expenses for used capital is desirable for future research. Following Baker et al. (2003), we exclude financial firms (i.e., firms with a one-digit SIC of six) and firm-years with a book value under \$10 million, but include all observations with data on capital reallocation and the KZ index.[31]

The combination of COMPUSTAT and IBES databases results in an unbalanced panel that covers the period between 1971 and 2005.[32] The full sample includes 30412 observations, for an average of 1601 observations per year. We use CR_t/AT_{t-1} as the scaled measure of capital reallocation, where AT denotes book assets (COMPUSTAT Annual Item 6). To reduce the influence of outliers, we Winsorize each of the variables used at the first and ninety-ninth percentile; i.e., we set all variables beyond these tolerances to the first and ninety-ninth percentile values, respectively. Our results hold qualitatively without Winsorizing the data. Table 7 reports summary statistics for CR^i_t/AT^i_{t-1}, LTG^i_t and KZ^i_t.

[28] Using the median value of LTG, as recommended by IBES, gives similar results.

[29] All financial variables from COMPUSTAT are adjusted to 1971 USD using CPI.

[30] For example, using data from the 1992 Census of Manufactures, Eisfeldt and Rampini (2008) found that firms in the smallest size decile rent more than 46 percent of their capital, while firms in the largest decile rent about 11 percent of their capital on average, and the fraction rented is monotonically decreasing across size deciles.

[31] Our main empirical empirical findings are robust to the inclusion of firms with book value below \$10 million.

[32] The details for how to merge COMPUSTAT and IBES databases are provided in a appendix available upon request.

Table 7. Summary Statistics

	mean	SD	max	min
CR_t^i/AT_{t-1}^i	0.0334	0.1076	0.6716	-0.1127
LTG_t^i	0.1812	0.0984	0.5367	0.0202
KZ_t^i	0.2462	1.2776	4.1729	-6.5283

6.2 Countercyclicality of Financial Frictions on Capital Allocation

We now provide evidence on the first prediction: Financially constrained firms acquire more capital in boom than unconstrained firms do, while the opposite is true in recession. Put differently, we should observe that capital reallocation for financially constrained firms is more volatile along business cycles than that for unconstrained firms. As mentioned above, this implication is the prerequisite for frictions on capital allocation to be countercyclical.

We use $CR_t^J \equiv \frac{1}{N^J}\sum_{i\in KZ^J} CR_t^i/AT_{t-1}^i$ to measure the average size of capital reallocation for firms whose mean value of KZ_t^i over the full sample period belongs to the J-th quintile, where N^J refers to the number of firms in the J-th quintile. $\widehat{CR}_t^J$ is the cyclical component of CR_t^J obtained by H-P filter. COMPUSTAT started to record acquisition (item 129) since 1971. Therefore, we have data on $\widehat{CR}_t^J$ from 1971 to 2005. Figure 7 plots $\widehat{CR}_t^1$ and $\widehat{CR}_t^5$ (i.e., size of total acquisition by firms in the bottom and top KZ quintiles, respectively), together with the H-P filtered real U.S. GNP, denoted by $\widehat{GNP}_t$. Note that sizes of capital reallocation before 1980 are much smaller than those afterwards. It is obvious in Figure 5 that after 1980, while both of $\widehat{CR}_t^1$ and $\widehat{CR}_t^5$ are procyclical, capital reallocation for firms in the bottom KZ quintile is much more volatile than that for firms in the bottom quintile.

[Insert Figure 5]

More precisely, Table 8 shows that the standard deviation of $\widehat{CR}_t^J$ is monotonically increasing in J. The increase of volatility is sizable: the variance of $\widehat{CR}_t^5$ more than doubles the variance of $\widehat{CR}_t^1$. Due to limited sizes of capital reallocation in COMPUSTAT in the 1970s, one may suspect that capital reallocation has a much smaller effect on business cycles before 1980. For this concern, Table 8 also reports results for the sub-sample period from 1981 to 2005. We see that for that period, the monotonicity of the standard deviation of $\widehat{CR}_t^J$ along J still holds.

Table 8. Financial Constraint and Standard Deviation of Capital Reallocation

	Full Sample (1971-2005)	Sub-sample (1981-2005)
$\widehat{CR}^1$	0.0050	0.0051
$\widehat{CR}^2$	0.0057	0.0073
$\widehat{CR}^3$	0.0064	0.0082
$\widehat{CR}^4$	0.0087	0.0098
$\widehat{CR}^5$	0.0117	0.0153

6.3 Asymmetric Impacts of News Shocks

It is natural to ask further what causes the countercyclicality of financial frictions on capital allocation. To this end, we test the second implication of our model: Prospects on an individual firm's future profitability affect constrained firms' capital acquisition, but not that of unconstrained firms. In other words, the presence of financial constraints allows changes in the firm-level earnings forecast of future profitability to affect current capital acquisition.

We apply the method of Baker et al. (2003) to test the implications. All firms in the sample data are classified into quintiles according to their mean value of KZ_t^i over the full sample period. For each KZ quintile, we estimate

$$\frac{CR_t^i}{AT_{t-1}^i} = a_i + a_t + b \cdot LTG_t^i + u_t^i, \tag{26}$$

where a_i and a_t are firm and year dummies, respectively. The hypothesis implies that the estimated coefficient b should be statistically insignificant for firms in lower KZ quintiles, while significantly positive for firms in higher KZ quintiles. Furthermore, firms that are more likely to be financially constrained should have a stronger sensitivity of capital reallocation to LTG than firms that are less likely to be financially constrained. Since KZ measures the likelihood of a firm being financial constrained, this hypothesis implies a monotonic increase of the estimated b along the KZ quintiles.

Table 9 presents the estimated results. As predicted by the theory, the estimates of b are positive and highly significant for the third to fifth quintiles, but not significant, or even negative, for the first two quintiles.[33] Moreover, there is a strong positive correlation between KZ and the effect of long-term growth forecasts on capital reallocation. The coefficient b rises monotonically from 0.087 in the third quintile to 0.154 in the bottom quintile. Hence, both the

[33] The negative estimated b may reflect the fact that firm-level variations in the expected future profitability contains information at the aggregate level. According to our model, news on aggregate future technological improvement causes capital to flow from financially unconstrained to constrained firms via the general equilibrium effect.

statistical significance and the monotonicity of the estimated b across KZ quintiles support our hypothesis regarding the asymmetric impacts of news shocks.

Table 9. Business Prospects and Capital Reallocation

KZ index	b	Obs.	Adj. R^2
Quintile 1	-0.0453^{*} (0.021)	6075	0.2224
2	0.0032 (0.021)	6084	0.1826
3	0.0857^{**} (0.023)	6086	0.1753
4	0.1194^{**} (0.026)	6078	0.2375
5	0.1544^{**} (0.032)	6089	0.2588

Note: ** and * stand for is significant at 1% and 5%, respectively. Robust standard errors are in parentheses.

One caveat for our estimation strategy is the endogeneity of the mean value of KZ_t^i over the full sample period, which we use to measure individual firms' likelihood of being financially constrained. This is because our constructed KZ index is potentially correlated with the error term, and in particular, firms' current earning profitability. As a robustness check, we classify firms based on their value of KZ_t^i at the first year they enters into our sample, which is not likely to be affected by individual firms' earnings profitability during our sample period. To compare, we run the same panel regression (26) for each KZ quintile. Column (1) of Table 10 shows that the estimated b for each KZ quintile are similar in magnitude to their counterparts in the baseline case.[34] Hence, our main findings are robust to the potential endogeneity of KZ.

Another caveat is the potential endogeneity for our key regressor of interest, LTG. Although IBES asks analysts to report LTG independent of the current state of the business cycle, LTG might still be correlated with the error term in (26) through information available to analysts. Specifically, the error term may contain a variable that affects capital reallocation and LTG simultaneously (e.g., cash flow shocks). This potential endogeneity tends to bias upward our estimation of b for each KZ quintile.

We pursue three strategies for addressing the endogeneity bias. First, we add in our regressions cash flow, which is often taken as a good control for fundamentals in the literature.[35]

[34] The reason for this similarity is that in our sample, the KZ_t^i at the first year a firm entered into our sample and the mean value of KZ_t^i over the full sample period is highly correlated (0.78). This indicates that the potential endogeneity of the mean KZ_t^i over the full sample period shall has a minor impact on the measured likelihood of being financially constrained and the classification of firms into quintiles.

[35] Specifically, we add the ratio of cash flow over AT_{t-1}^i (COMPUSTAT Annual Item 14 + Item 18) to the regression as an additional control.

Column (2) of Table 10 shows that the results are qualitatively the same as the baseline results. In particular, the statistical significance and monotonicity of the estimated b across KZ quintiles remain unchanged.

Our second strategy is to explore the potential correlation between LTG and the error term. Note that b is not likely to be negative (i.e., an increase of future profitability is not likely to reduce capital reallocation). Given this feature, the insignificant or negative estimates of b for the top two quintiles in Table 9 and column (1) and (2) of Table 10 suggests that the upward bias of the estimate of b is negligible at least for the top two quintiles. An alternative measure for future profitability is firm's Q. Column (3) of Table 10 shows that the estimates of b for the top two quintiles turn positive and significant when we replace LTG in (26) with "long-run real Q" constructed by the way proposed in Cummins et al. (2006).[36] The significant upward bias suggests the long-run real Q (containing two-year-ahead earnings forecasts) tends to be more correlated with the error term than LTG does.

Table 10. Robustness Check

KZ index	(1)	(2)	(3)
Quintile 1	-0.0027	-0.0493^{*}	0.0034^{*}
	(0.023)	(0.021)	(0.002)
2	0.0212	-0.0026	0.0094^{**}
	(0.022)	(0.021)	(0.002)
3	0.0842^{**}	0.069^{**}	0.0197^{**}
	(0.024)	(0.023)	(0.003)
4	0.1010^{**}	0.1016^{**}	0.0345^{**}
	(0.027)	(0.026)	(0.003)
5	0.1434^{**}	0.1126^{**}	0.0412^{**}
	(0.030)	(0.032)	(0.004)

Note: ** and * stand for significant at 1% and 5%, respectively. Robust standard errors are in parentheses. In Column (1), we classify firms based on their value of KZ_t^i at first year they enter into our sample. In Column (2), we add a ratio of cash flow over AT_{t-1}^i as the control variable. Column (3) drops control variables in Column (2), but replaces LTG with the long-run real Q in Cummins et al. (2006). We use the sample mean of KZ_t^i to classify firms in Column (2) and (3). Using first-year KZ_t^i gives qualitatively similar results.

Finally, our empirical strategy aims to test whether the estimates of b in (26) increase along quintiles. The observed increasing pattern of estimated b in Table 9 would be misinterpreted only if the endogeneity bias would also increase along quintiles. In Appendix 8.4, we derive explicitly the condition for the endogeneity bias to be non-increasing along quintiles. The condition shows that the increasing biases can only occur under very restrictive assumptions.

[36] The long-run real Q computes the two-year-ahead expected market value for each firm according to two-year-ahead earnings forecasts and the long-term growth forecasts LTG. One-year-ahead earnings forecasts are excluded since they are most likely affected by the current state of the economy.

Therefore, we conclude that our finding regarding the asymmetric impacts of news on capital acquisition by constrained and unconstrained firms is robust to the potential endogeneity of LTG.

Our firm-level evidence regarding the asymmetric impacts of news is consistent with the above macro evidence on capital allocation over the business cycles. This is because LTG_t^i in boom periods are, on average, higher than those in recessions. For instance, the mean of LTG_t^i across firms in the period of 1997-2000 is 23.71, much higher than that of 17.57 in the period of 1991-1994. Therefore, asymmetric impacts of news on capital acquisition across financially constrained and unconstrained firms, together with the procyclical movements of LTG_t^i, provide an explanation for the countercyclicality of financial frictions documented in the previous subsection.

In summary, we find that financial frictions on capital allocation at firm-level are countercyclical. Moreover, our empirical findings suggest a key element for business prospects to affect capital reallocation−the presence of financial constraints. These, together with the findings of Basu and Fernald (2000), indicate the very channel described by our model for resource allocation to affect aggregate TFP fluctuations over business cycles: variations in financial frictions, triggered by news shocks, lead to resource reallocation and, therefore, aggregate TFP fluctuations over the business cycles.

6.4 Frictions on New Capital Investment

Our model assumes away financial frictions on investment. In reality, a relaxation of financial constraints might allow a firm to expand its production scale through an additional channel: investing new capital. This channel has been viewed in the literature as the leading candidate for financial frictions to play a role in business cycles. In this subsection, we examine further the empirical relevance of financial frictions on new investment over business cycles.

To establish our empirical strategy, note that most business cycle studies that resort to financial frictions on new investment share a common feature: changes in the market prices of assets affect the degree of financial frictions via borrowing producers' net worth. Since market prices of assets are largely driven by prospects on future investment profitability, these models bear similar implications that the arrival of good (bad) news about future profitability shall relax (tighten) financial constraints. Accordingly, the presence of financial constraints magnifies the impacts of news on new capital investment.[37] If financial frictions on investment are empirically relevant, we should therefore observe a significantly larger response of new

[37] Note that even if financial constraints are absent, news about future profitability affects the first-best investment level.

capital investment to business prospects about future profitability for financially constrained firms than unconstrained ones. Hence, to test their empirical relevancy, we ask to what extent the presence of financial frictions affects the impact of business prospects on investment, and then compare the results with their counterparts in Table 9.

To make the comparison sharp, we follow exactly the same estimation strategy as before. The impact of business prospects on investment is estimated across firms along different KZ quintiles. The sample firms in each KZ quintile remain unchanged as those in the empirical exercise on capital reallocation.[38] We run the same panel regressions as (26). The only exception is that the dependent variable now becomes investment, measured as expenditure on new capital investment, $CAPEX_t^i$ (COMPUSTAT Annual Item 128), scaled by one-period-lag book assets, AT_{t-1}^i (Item 6).

$$\frac{CAPEX_t^i}{AT_{t-1}^i} = a_i + a_t + b \cdot LTG_t^i + u_t^i. \tag{27}$$

Here a_i and a_t are firm and year dummies, respectively.

Table 11 reports the estimation results. Compared with the estimated elasticity of capital reallocation to business prospects in Table 9, we find two key differences in the patterns of estimated b for new capital investment. First, for all quintiles, the estimates of b for new capital investment are highly significant. By contrast, in Table 9, the estimates for capital reallocation significantly differ from zero only for the top three KZ quintiles, that is, firms that are likely or definitely financially constrained. Second, while the estimated b for capital reallocation monotonically increases along KZ quintiles (Table 9), this pattern disappears completely when the dependent variable changes to new capital investment (Table 11). In fact, the estimates turn out to be rather stable across quintiles, ranging from the lowest of 0.12 to the highest of 0.17.[39]

[38] We exclude those firm-year observations for which investment data are missing from our sample firms for capital reallocation. This results in a sample size slightly smaller.

[39] We also perform robustness check, following the same procedure as that in our previous exercises for capital reallocation (Table 10). Our two key findings remain unchanged. The results are available upon request.

Table 11: Business Prospects and New Capital Investment

KZ index	b	Obs.	Adj. R^2
Quintile 1	0.1218** (0.012)	6033	0.5645
2	0.1558** (0.013)	6027	0.5635
3	0.1305** (0.014)	6023	0.5540
4	0.1743** (0.016)	6036	0.6115
5	0.1588** (0.170)	6045	0.6379

Note: ** and * stand for is significant at 1% and 5%, respectively. Robust standard errors are in parentheses.

It is not surprising that new capital investment reacts significantly to LTG. As predicted by the standard theory, higher future profitability implies a larger first-best capital stock in the future and, therefore, more investment in the current period. Nevertheless, if financial frictions distort a firm's production scale through new capital investment, we should expect to see monotonically increasing estimates of b along KZ quintile in Table 11, as those in Table 9. To the opposite, the estimates exhibit non-monotonicity and are rather stable across quintiles. The very different patterns of estimated b in Table 9 and 11 help to distinguish the empirical relevance of two channels through which financial frictions affect firms' production scale over business cycles. In particular, we fail to find evidence for financial frictions to play a role through new capital investment, despite its wide acknowledgement as one of the main channels in the business cycle literature. This contrast greatly enhances the empirical plausibility of the channel highlighted in the present paper: Financial frictions on capital reallocation serve as a transmission mechanism for primitive shocks to affect aggregate productive efficiency.[40]

In summary, our empirical results strongly support the importance of variations in financial frictions on capital reallocation, rather than new capital investment, for individual firms' production scales. This, together with its countercyclicality, indicates that financial frictions on capital allocation is potentially important, and is empirically more plausible than financial frictions on new investment as a transmission mechanism for primitive shocks to translate into aggregate TFP fluctuations.

[40] We conjecture that the different patterns of the estimated b between capital acquisition and new capital investment might be due to the trade-off between the time-to-build feature of new investment and the complementarity between new vintages of capital and new technology. We leave this issue for future research.

7 Conclusion

This paper argues that financial frictions on capital allocation, rather than on new capital investment, are important as a transmission mechanism for primitive shocks to translate into aggregate TFP fluctuations. We show in a calibrated model that variations in financial frictions in response to news shocks can trigger sizable fluctuations in aggregate TFP before the actual technology change is realized. The TFP fluctuations originating from capital reallocation, furthermore, lead to business cycles by allowing positive comovement among current output, consumption, investment, and hours worked. This positive comovement is, however, difficult to obtain when financial frictions are imposed on new capital investment. Empirically, we find that the responses of capital acquisition to prospects about future profitability are significantly larger for firms more likely to be financially constrained, while such a pattern does not exist for new capital investment. Capital acquisition of constrained firms, furthermore, is found to be more procyclical than that for unconstrained ones. Therefore, both our theory and empirical evidence support strongly the role of financial frictions on capital allocation as a transmission mechanism of TFP fluctuations over U.S. business cycles.

Our work can be considered as a first step towards understanding TFP fluctuations over business cycles. The model developed here, as a result, has abstracted from a number of important issues. For example, in our model, entry and exit are exogenous. An endogenous entry and exit decision à la Hopenhayn (1992) can be introduced to explore the importance of financial frictions for aggregate TFP via firm entry and exit. We conjecture that introducing this extensive margin will amplify the response of aggregate TFP to primitive shocks such as news shocks. A perhaps more important issue is that we abstract from individual firm dynamics and how they interact with frictions on capital allocation. These abstractions also make the model silent on which firms are financially constrained. One can, instead, consider a model with a long-term financial contract to endogenize firm size distribution. It would be interesting to see how the presence of a long-term contract affects our results. Also, such a framework may help to understand how primitive shocks are propagated over business cycles.

Aside from the implications for TFP fluctuations, our model provides an alternative view of how acquisitions are related to firm values, an issue that has been often addressed in the finance literature (e.g., Jovanovic and Rousseau, 2002, and Shleifer and Vishny, 2003). One caveat is that firms in the present model are evaluated by the discounted sum of future profits. An interesting extension of the model would be to allow for production-based asset pricing, so that stock market valuations of firms and reallocations of capital interact over time. This might eventually explain the puzzling joint behavior of aggregate TFP and stock prices found by Beaudry and Portier (2006).

8 Appendix

8.1 Enforcement Constraint

The renegotiation process described here follows closely from Jermann and Quadrini (2006). Assume that production of a type-h project at each period requires an amount of working capital, denoted as $f_t = D\left(k_t^h\right)$ (or $D\left(k_t^h, h_t^h\right)$ in the benchmark economy), with $D'(\cdot) > 0$. Working capital consists of liquid funds that are used at the beginning of time t and are recovered at the end of time t, after all transactions have been completed. Because this is an intra-period loan, the net interest payment is zero.

Entrepreneurs have the ability to divert working capital and default.[41] Once the entrepreneur defaults, the lender can take over the control right of the project and recover a fraction φ of the future project value, denoted as V_{t+1}^h, which is the simply the present discount value of the project profits from tomorrow on. Here, the underlying assumption is that only the entrepreneur has the required talent to run this project efficiently. Denote by ω the bargaining power of the entrepreneur and by $1-\omega$ the bargaining power of the lender. Bargaining is over the repayment of the debt, denoted as $\widehat{f}_t$. If they reach an agreement, the entrepreneur gets $f_t - \widehat{f}_t + V_{t+1}^h$, and the lender gets $\widehat{f}_t$, If there is no agreement, the entrepreneur gets f_t and the lender gets φV_{t+1}^i. Therefore, the net value for the entrepreneur to reach an agreement is $V_{t+1}^h - \widehat{f}_t$ and the net value for lender is $\widehat{f}_t - \varphi V_{t+1}^h$. The bargaining problem solves:

$$\max_{\widehat{f}_t} \left\{ \left(V_{t+1}^h - \widehat{f}_t\right)^{\omega} \left(\widehat{f}_t - \varphi V_{t+1}^h\right)^{1-\omega} \right\}$$

Taking the first-order condition, we get $\widehat{f}_t = \left[1-\omega\left(1-\varphi\right)\right] V_{t+1}^h$. Incentive compatibility requires that the value of non-default for the entrepreneur, V_{t+1}^h, should be no less than the value of default, which is $f_t - \widehat{f}_t + V_{t+1}^h$. Hence, we have

$$\left[1-\omega\left(1-\varphi\right)\right] V_{t+1}^h \geq f_t$$

Denote $\left[1-\omega\left(1-\varphi\right)\right]$ as θ. Then we get (1) or (13) in the benchmark model.

[41] Similarly, Hart and Moore (1998) assume that beyond the project cost, a fraction of the loan that the debtor receives from the creditor represents the non-recourse financing, which is not seizable by the creditor.

8.2 Definition of Recursive Competitive Equilibrium for the Benchmark Economy

This section sketches out the definition of the recursive competitive equilibrium for our benchmark economy. To simplify notation, we abstract from population and denote lower-case variables as individual variables and upper-case variables as aggregate variables. In our benchmark economy with news shocks on Z_t, the state variables for the households are $s_t = \left(Z_t, \epsilon_t^Z, k_t, K_t\right)$ or simply (Z_t, Z_{t+1}, k_t, K_t) since next-period aggregate technology is perfectly predictable by (8). Because entrepreneurs' optimization problems at each period are static, we need only specify the household's problem recursively. The household's problem can be rewritten as

$$v\left(Z, Z^{'}, k, K\right) = \max_{c,i,h} \left\{u\left(c, h\right) + \beta E\left[v\left(Z^{'}, Z^{''}, k^{'}, K^{'}\right) \mid Z^{'}\right]\right\}$$

subject to

$$\begin{aligned} c + i &= \left(r\left(Z, Z^{'}, K\right) + \delta\right) k + w\left(Z, Z^{'}, K\right) h. \\ k^{'} &= \left(1-\delta\right) k + i \\ K^{'} &= \left(1-\delta\right) K + I\left(Z, Z', K\right) \\ \log Z^{'} &= \rho \log Z + \epsilon^Z \end{aligned} \tag{28}$$

A recursive competitive equilibrium for this economy consists of a value function, $v\left(Z, Z^{'}, k, K\right)$; a set of decision rules $c\left(Z, Z^{'}, k, K\right)$, $i\left(Z, Z^{'}, k, K\right)$, $h\left(Z, Z^{'}, k, K\right)$ for the household; a corresponding set of aggregate per capita decision rules, $C\left(Z, Z^{'}, K\right), I\left(Z, Z^{'}, K\right), H\left(Z, Z^{'}, K\right)$; a set of decision rules for the entrepreneurs, $K^h\left(Z, Z^{'}, K\right)$, $H^h\left(Z, Z^{'}, K\right)$, $K^l\left(Z, Z^{'}, K\right)$, $H^l\left(Z, Z^{'}, K\right)$, $c^h\left(Z, Z', K\right)$, $c^l\left(Z, Z', K\right)$and factor prices functions $r\left(Z, Z^{'}, K\right)$, $w\left(Z, Z^{'}, K\right)$, such that these functions satisfy

1. The household's problem (28);
2. The entrepreneurs' problem;
3. The consistency of individual and aggregate decisions - that is, $c\left(Z, Z^{'}, k, K\right) = C\left(Z, Z^{'}, K\right)$, $i\left(Z, Z^{'}, k, K\right) = I\left(Z, Z^{'}, K\right)$ and $h\left(Z, Z^{'}, k, K\right) = H\left(Z, Z^{'}, K\right)$.
4. The aggregate resource constraint

$$\begin{aligned} & C\left(Z, Z^{'}, K\right) + \eta c^h\left(Z, Z', K\right) + \left(1-\eta\right) c^l\left(Z, Z', K\right) + I\left(Z, Z^{'}, K\right) = Y\left(Z, Z^{'}, K\right) \\ = \; & \eta A^h\left(\left(K^h\left(Z, Z^{'}, K\right)\right)^{\alpha}\left(H^h\left(Z, Z^{'}, K\right)\right)^{1-\alpha}\right)^{\mu} \\ & + \left(1-\eta\right) A^l\left(\left(K^l\left(Z, Z^{'}, K\right)\right)^{\alpha}\left(H^l\left(Z, Z^{'}, K\right)\right)^{1-\alpha}\right)^{\mu}, \forall\left(Z, Z^{'}, K\right). \end{aligned}$$

8.3 Impulse Response to News on the Type-h Technology χ_t^h

The U.S. boom in the 1990s was fueled largely by the optimism of a "New Economy," represented by technological breakthroughs in the computer sector and their wide usage in other sectors. Therefore, it is natural to think of one candidate for primitive shocks as news on future advances of technology in the high-tech industry.

We consider news shocks on type-h project-specific technology. Specifically, we let Z_t and χ_t^l remain constant (equal to their mean) and assume all projects $i \in [0, \eta]$ share the same project-specific technology, which are subject to news shocks specified as

$$\log \chi_{t+1}^h = (1-\rho)\log \bar{\chi}^h + \rho \log \chi_t^h + \epsilon_t^{\chi^h}, \tag{29}$$

where $\epsilon_t^{\chi^h}$ denotes information innovation on the next-period technology, χ_{t+1}^h. Here, again, we assume that news shocks in the current period are uncorrelated with current technology χ_t^h; rather, it is a perfect signal on the future technology innovation observed by all agents in this economy.

To compare the results from news shocks on aggregate and project-specific technology, we keep the same parameterization as in the baseline case, except for the variance of information innovations, denoted by $\sigma_\epsilon^{\chi^h}$. We choose the value of $\sigma_\epsilon^{\chi^h}$ such that the standard deviation of the log of H-P detrended TFP simulated from the model is equal to the corresponding value in annual U.S. data. The calibration gives $\sigma_\epsilon^{\chi^h} = 2.14\%$.

Figure 6 shows the impulse responses of various variables to a one-percentage news shock to type-h project specific technology arriving at period 1. Although the dynamics are qualitatively similar, with news shocks on χ^h, the contribution of the reallocation effects to aggregate TFP fluctuation is larger. In particular, the initial response of aggregate TFP is now about half of the increase in aggregate TFP when the technology improvement is realized. Moreover, the reallocation effects now becomes more persistent compared with the baseline case. The intuition is as follows. Given χ^l unchanged, capital demanded by type-h projects will be rented at a relatively cheaper price than with news shocks to aggregate technology. This implies a larger increase in future profit for type-h projects. A higher project value, accordingly, relaxes the financial constraint by a larger extent and induces more resource to flow from type-l to type-h projects. Financial frictions on capital allocation, measured by the gap in $TFPR$, reduce more sharply by 0.66 percent on impact. Finally, the initial response of macroeconomic variables is also remarkable. The news drives the initial aggregate output by 0.87 percent, more than half of the output increase when the technological improvement is realized at period 2.

[Insert Figure 6 Here]

8.4 The Endogeneity Bias of LTG

In this subsection, we derive explicitly the condition for the endogeneity bias to be non-increasing along quintiles. For notational ease, let us consider the simplest version of our estimation specification:

$$\left(\frac{CR_{it}}{AT_{it-1}}\right)^J = a^J + b^J \cdot LTG_{it}^J + u_{it}^J. \tag{30}$$

Here J stands for the $J-$th quintile. For notational simplification, we now drop the time subscript hereafter. We assume the error term to entail two components:

$$u_t^J = \varepsilon_t^J + \phi \cdot v_t^J. \tag{31}$$

The first term ε_t^J is standard and uncorrelated with LTG_t^J, while the second term v_t^J is an unobservable shock. Note that according to our theory, after controlling for future profitability, which governs the tightness of financial constraints, the response of capital reallocation to v_t^J shall be the same across quintiles. Therefore, we let the impact of v_t^J on capital reallocation (captured by the coefficient ϕ) be the same across quintiles. To highlight the endogeneity problem, we further assume that v_t^J affects LTG_t^J in the following way:

$$LTG_t^J = c^J \cdot v_t^J + n_t^J, \tag{32}$$

where n_t^J, which can be interpreted as news shocks, is uncorrelated with v_t^J and ε_t^J. The structural assumption (32) reflects your concern: LTG might depend not only on pure news, but also on the current information which influences the decision of capital reallocation simultaneously (captured by v_t^J and equation 31). For example, v_t^J can be the current profitability, which may affect analysts' long-run earnings forecast (as indicated by your comment). Note that we allow the impacts of v_t^J on LTG (captured by the coefficient c^J) to be different across quintiles to make our analysis more generous.

Under the assumptions of (31) and (32), the OLS estimator of b^J in (30) gives

$$\begin{aligned} \hat{b}^J &= b^J + \frac{cov\left(LTG_t^J, u_t^J\right)}{var\left(LTG_t^J\right)} \\ &= b^J + \frac{\phi \cdot c^J \sigma_v^2}{\left(c^J\right)^2 \sigma_v^2 + \sigma_n^2}. \end{aligned} \tag{33}$$

where σ_v^2 and σ_n^2 stand for the variance of v_t^J and n_t^J, respectively. It is clear from equation (33) that the observed monotonically increasing pattern of $\hat{b}^J$ might be driven by a monotonic increasing pattern of its second argument, rather than the first one. However, two remarks are in order to suggest that this situation may not happen. First, the endogeneity biases $\hat{b}^J$ upward, as we expect ϕ to be positive. Nevertheless, if there is no clear pattern of c^J across quintiles, the bias would cause no statistically significant impact on the difference of $\hat{b}^J$ since the endogeneity of LTG biases the OLS estimator equally across quintiles. Second, even if c^J indeed changes monotonically along quintiles, its impact on the second argument of $\hat{b}^J$ and, therefore, the difference of $\hat{b}^J$ across quintiles is still ambiguous. For instance, suppose that c^J is increasing in J. The second argument of $\hat{b}^J$ would increase with c^J and, hence, J, only if $\sigma_n/\sigma_v > c^J$ for all c^J.

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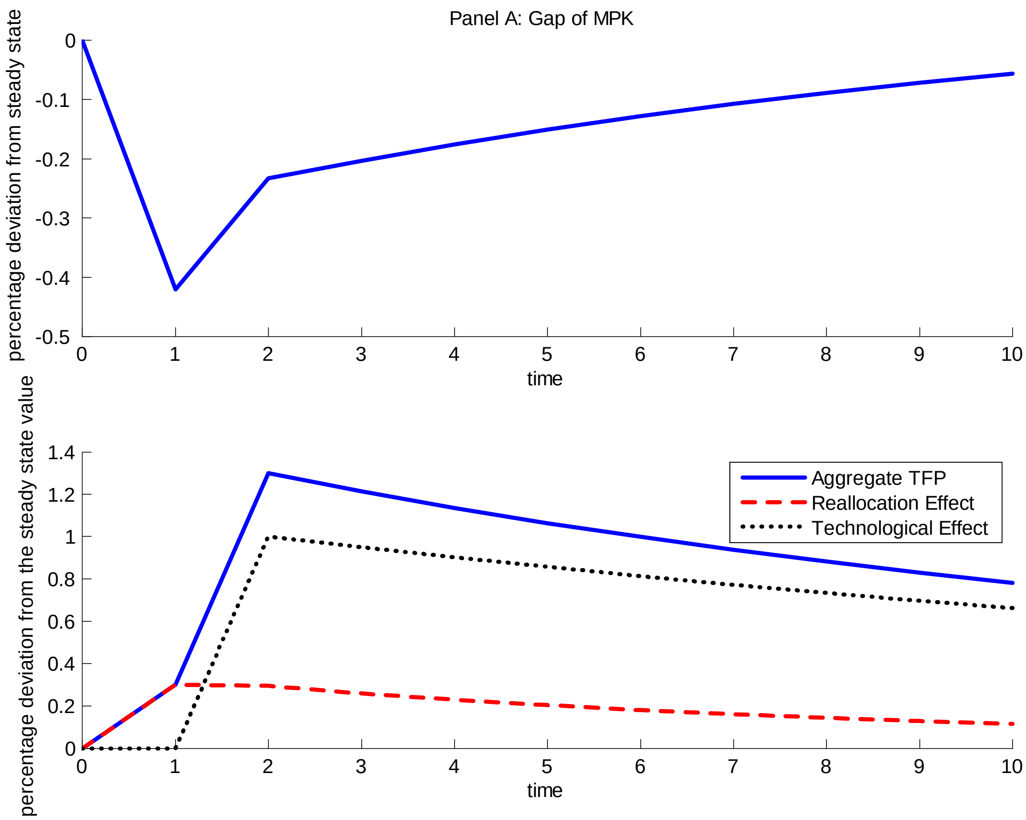

Figure 1: Response of Aggregate TFP and its Components to News Shock on Aggregate Technology in the Economy w/o Labor.

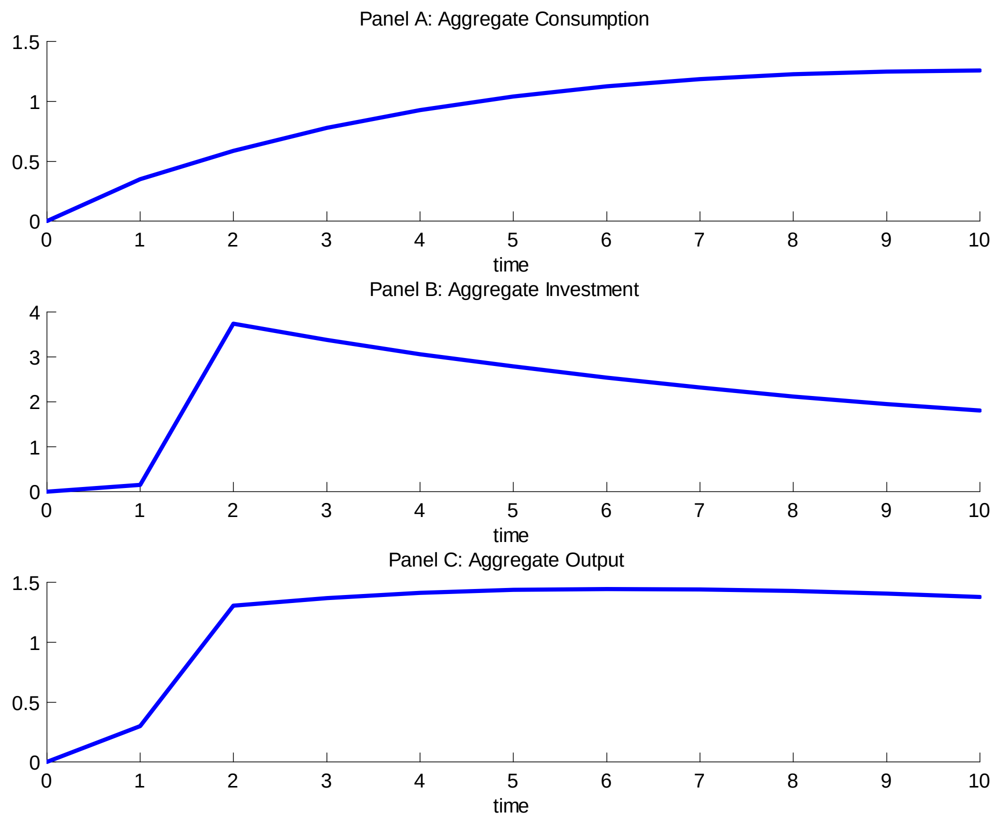

Figure 2: Percentage Deviations from the Steady State Value of Consumption, Investment and Aggregate Output in Response to News Shock on Aggregate Technology in the Economy w/o Labor.

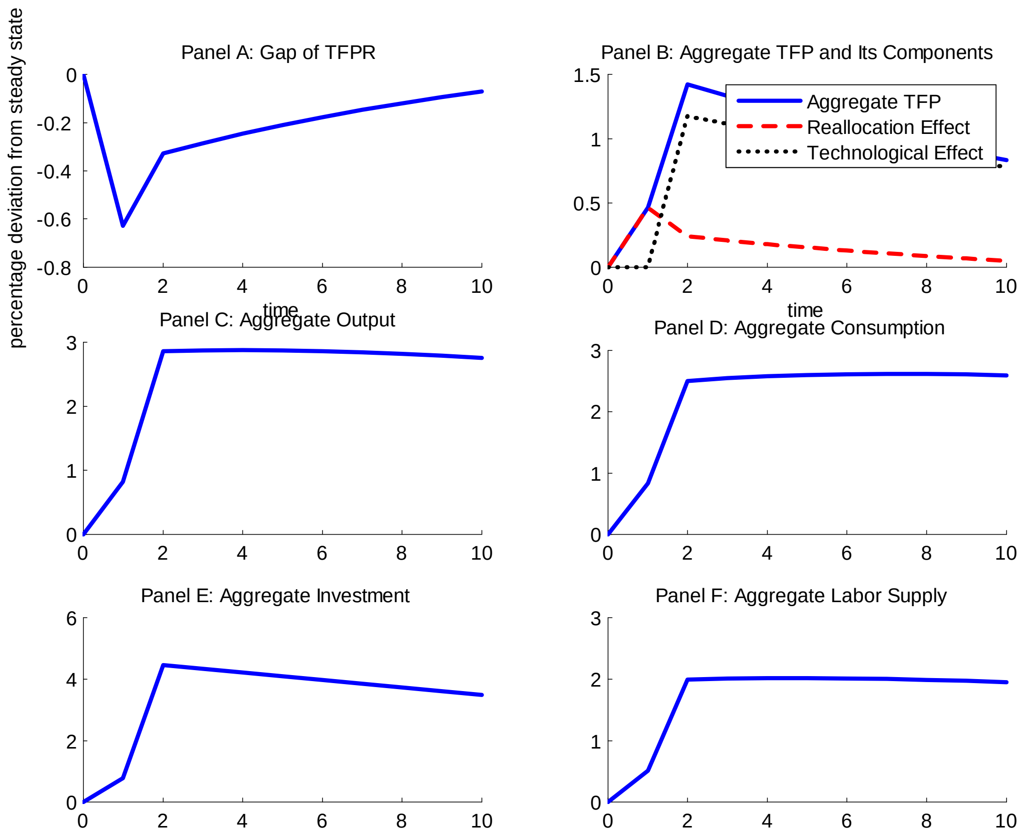

Figure 3: Impulse Responses to News Shocks on Aggregate Technology in the Benchmark Model

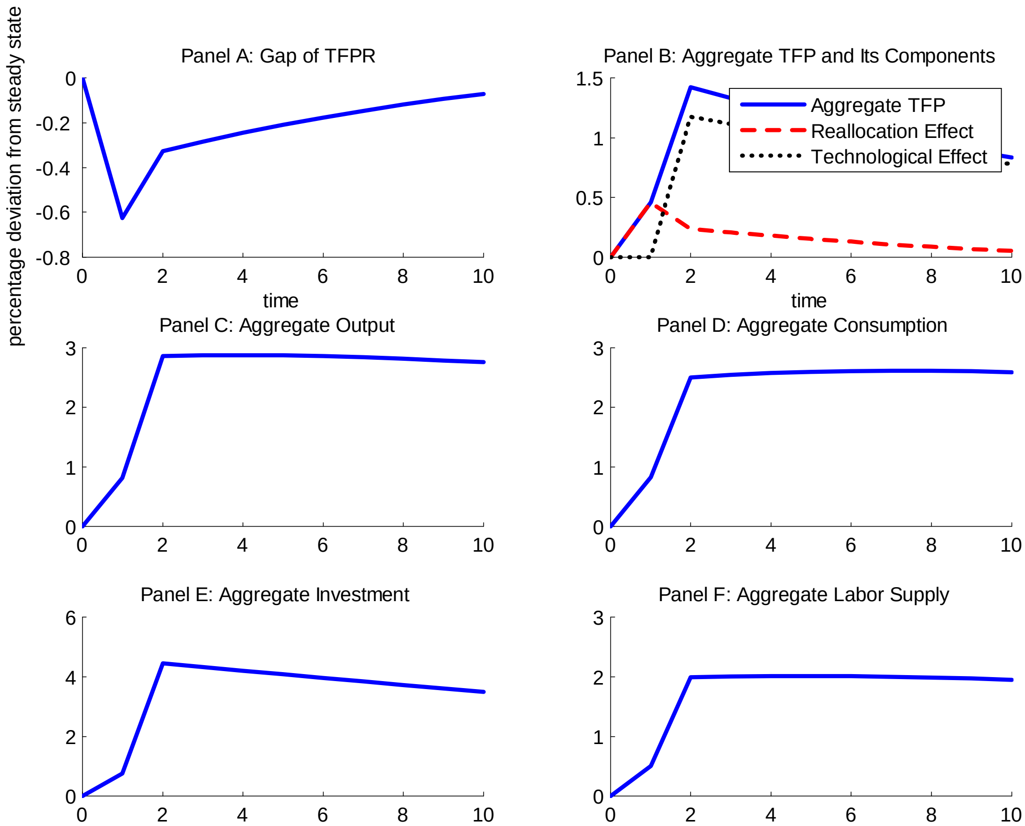

Figure 4: Impulse Responses to News Shocks on Aggregate Technology in the Benchmark Model with $\eta = 0.25$.

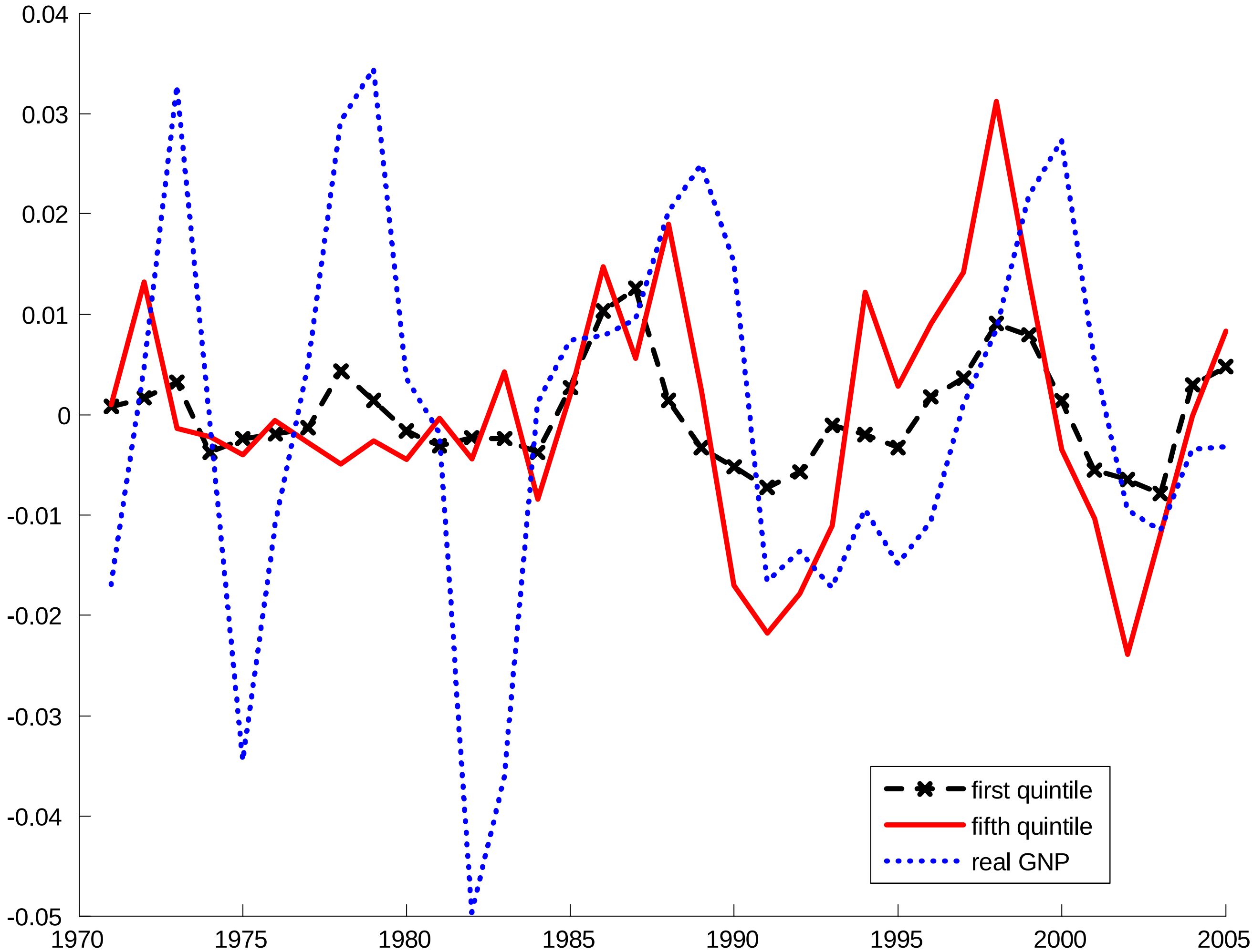

Figure 5: Capital Reallocation over the U.S. Business Cycles for Different KZ Quintiles.

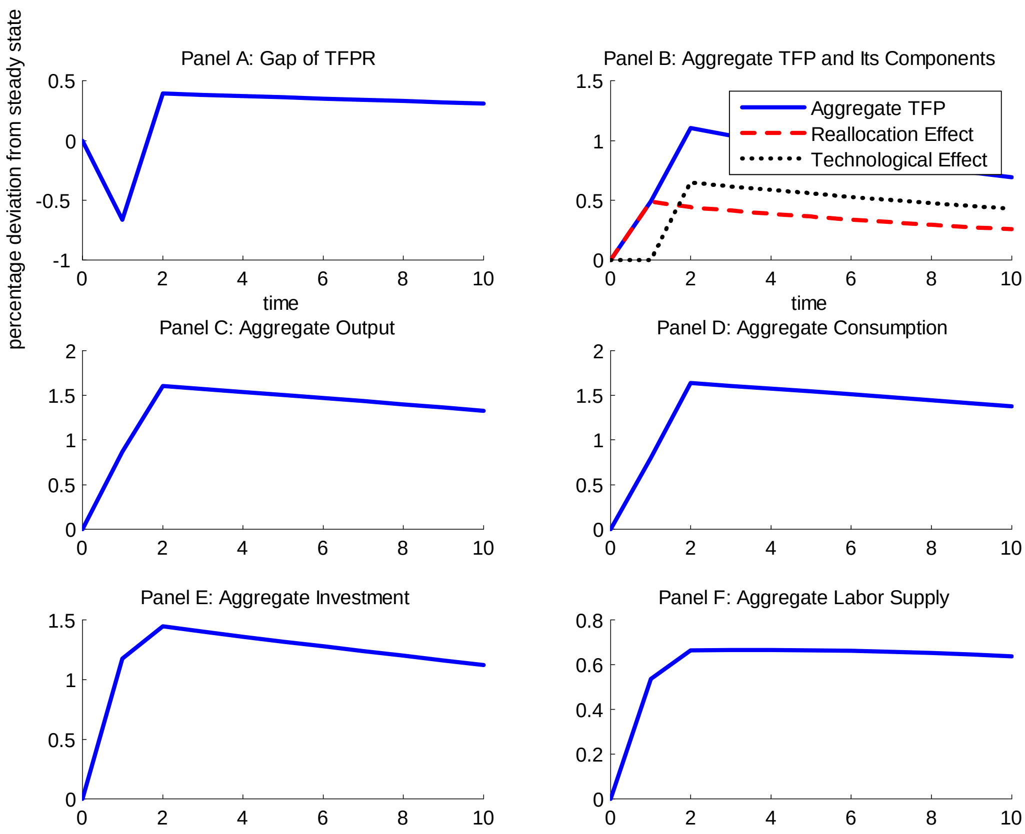

Figure 6: Impulse Responses to News Shocks on Project-Specific Technology in the Benchmark Model