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 news shocks to drive aggregate TFP fluctuations. We show that in an economy calibrated to U.S. data, variations in financial frictions on capital allocation in response to news about future technology can generate aggregate TFP fluctuations and, thus, trigger business cycles before the actual technological change is realized. Using the COMPUSTAT dataset, we find that the relative capital productivity of financially constrained to unconstrained firms is highly countercyclical. Moreover, our VAR analysis shows that news shocks can account for a substantial fraction of the relative capital productivity fluctuations over business cycle frequencies.

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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. One promising candidate for understanding TFP fluctuations is financial friction on inputs. The presence of such friction naturally distorts resource allocation at the disaggregate level and, thus, reduces aggregate productive efficiency. Accordingly, variations in financial frictions, by varying the degree of resource misallocation, may translate primitive shocks 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 that are, by construction, uncorrelated with the current production technology, but, at the same time, affect financial frictions. Our theory shows that endogenous variations in financial frictions in response to such primitive shocks can trigger and amplify aggregate TFP fluctuations and business cycles through capital reallocation.

The key ingredient of our model is a collateral constraint that is only binding for entrepreneurs with insufficient net wealth. Accordingly, in our economy, there are two types of projects: One is financially constrained, and the other is not. The production scale of a constrained project, moreover, depends positively on the future project value. The asymmetry of the financial constraint 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 technological improvement. Specifically, the arrival of good news causes an immediate jump in the project value by increasing future profitability of the constrained projects. 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 the current aggregate TFP. The TFP fluctuation, in turn, leads to business cycles by allowing positive comovement among current output, consumption, investment, and hours worked.

To evaluate the quantitative implications of our model, we calibrate the economy to U.S. data. Simulation results indicate that our proposed transmission mechanism of TFP fluctuations can be quantitatively important. The magnitude of the increase in TFP on impact to a positive news shock, which is driven purely by capital reallocation, is about one fifth of the increase in technology when the technological improvement is materialized. Moreover, counterfactual experiments suggest that in our model, financial frictions on capital allocation is the key to trigger TFP fluctuations on impact to news shocks and, thus, positive comovement among macro variables.

The theory delivers two empirical predictions. First, the relative capital productivity of the constrained firms to the unconstrained is countercyclical. Second, the relative capital productivity, a measure of capital misallocation, responds negatively to news shocks on future technology. To test the two hypotheses, we use the COMPUSTAT dataset to estimate the capital productivity gap between constrained to unconstrained firms. Firms are classified into constrained and unconstrained groups by various financial constraint indices. We find that, on average, the constrained firms are more productive than the unconstrained in terms of revenue-based capital productivity. Moreover, consistent with the first prediction, the relative capital productivity between the two groups has a correlation coefficient with GDP of -0.66. Although the observation of countercyclical productivity dispersion is not new (see, e.g., Eisfeldt and Rampini, 2006; Kehrig, 2010), by documenting the cyclicality of the relative productivity of constrained to unconstrained firms, our evidence highlights the role of financial frictions in driving the cyclicality. We then explore empirically the response of our measured capital misallocation to news shocks that are identified through the methodology of Beaudry and Portier (2006). The structural VAR estimation shows that, consistent with our theory, news shocks have a persistent negative impact on the measured capital misallocation and can explain a substantial fraction of its fluctuations over business cycle frequencies. We view the empirical finding as a non-trivial contribution to the literature.

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 aggregate capital investment. 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 a shift of capital and labor from the consumption-good to the investment-good sector, implying that consumption and investment comove negatively.[1] In our model, by contrast, relaxing the financial constraint can trigger an immediate expansion of TFP by varying capital allocation across firms of different capital productivity. This makes the positive comovement of macro aggregates feasible.

This paper contributes to the literature on financial frictions. It has long been argued that frictions in financial markets are important for business cycles.[2] More recently, researchers have started to pay attention to financial markets frictions in the last recession (see, for example, Christiano, Motto and Rostagno, 2010; Jermann and Quadrini, 2011, 2012; Arellano, Bai and Kehoe, 2011). Despite this widely accepted view on the importance of financial frictions, their effects through distorting aggregate investment have been found to play quantitatively minor roles in driving economic fluctuations.[3] Our paper, instead, focuses on how financial frictions affect capital allocation at the disaggregate level. Khan and Thomas (2011) and Shourideh and Zetlin-Jones (2012) are another examples which study the effects of financial frictions on capital misallocation and productivity fluctuations over business cycles. These two papers, nonetheless, explore the role of financial shocks, while we examine how financial frictions on capital allocation respond to news shocks from both theoretical and empirical perspectives.

Our paper also contributes to the recent discussion on how news shocks can trigger business cycles. On empirical grounds, the evidence in Beaudry and Portier (2006) indicates that innovations in future technological opportunities are largely anticipated. More recently, 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. However, these observations are at odds with standard business cycle models, in which mere changes in expectation about future productivity are hard to generate comovement among consumption, investment

[1] 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 in the investment-good sector. The proof is available upon request.

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

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

and hours worked due to a lack of change in the current TFP.[4] Several studies have explored the effects of news shocks on an economy with financial frictions. Similar to our model, in both Gilchrist and Saito (2006) and Kabayashi, Nakajima and Inaba (2007), news shocks lead to variations in financial frictions through asset pricing. Neither paper, however, has capital misallocation at disaggregate levels, which serves as the key transmission mechanism for news shocks to drive aggregate TFP fluctuations.[5]

Finally, this paper is related to a growing literature studying the role of particular frictions on resource allocation and TFP (e.g., Erosa and Hidalgo Cabrillana, 2007; Guner, Ventura, and Xu, 2008; Restuccia and Rogerson, 2008; and Hsieh and Klenow, 2009). Much of the literature emphasizes the role of frictions in the cross-country difference in long-run TFP and, therefore, abstracts from the dynamics of such frictions. Buera and Shin (2008) show the persistent effect of financial frictions on economic development via resource allocation. Our paper focuses, instead, on TFP fluctuations over business cycles.

The paper is organized as follows. In Section 2, we present our main idea in a simple model without labor and characterize the model analytically. 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 and quantify the role of financial frictions in aggregate TFP fluctuations. We then conduct a robustness check to alternative model parameterization and specifications. Using firm-level data, Section 6 tests the two empirical predictions of our theory. Section 7 concludes. The Appendix includes the proof of a key proposition, a description of data sources, a robustness check of our empirical results, as well as variable definition. The Technical Appendix, available from our web pages, includes the definition of the recursive competitive equilibrium and proof of various lemma and propositions in Section 2.

[4]See, for example, Danthine and Donaldson and Johnsen (1998), Beaudry and Portier (2004) and Christiano, Ilut and Rostagno (2010) and Auray, Gomme and Guo (2012).

[5]Another potential source of the observed TFP fluctuations in response to news shocks is variations in capital utilization. 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).

2 A Simple Economy

In this section, we describe a model that abstracts from entrepreneur saving, productivity uncertainty and labor input (referred to as "a simple economy") to highlight the main mechanism of the paper. A full-blown model with richer business cycle ingredients will be provided in the next section.

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

Projects are classified into two categories, according to whether working capital (or liquid funds) is needed for production. Specifically, a fraction η of projects, denoted as type-c projects, require working capital before production takes place. We assume that the size of the working capital required, denoted as $D(k_t^c)$, increases with the capital deployed in a type-c project, denoted as k_t^c. $D'(\cdot) > 0$ and $D''(\cdot) < 0$. For the remaining $1-\eta$ fraction of projects, referred to as type-u projects, working capital is not necessary. In the simple model, entrepreneurs are risk-neutral and have no access to savings. So, an entrepreneur's consumption is equal to the profits of her project.

2.1 Project Financing and Entrepreneurs' Problems

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

$$y_t^i = Z_t F\left(k_t^i\right), \tag{1}$$

where k_t^i is capital in a single type-i project, Z_t is the aggregate technology, $F'(\cdot) > 0$ and $F''(\cdot) < 0$. Two remarks are in order. First, there is no uncertainty for the aggregate technology in the simple economy. We will let Z_t follow a stochastic process in the full-blown economy in Section 3. Second, the concavity of F implies that the revenue function displays decreasing returns to scale, which can be rationalized by assuming limited managerial resources, as in Lucas (1978). Alternatively, the concavity of the revenue function may come from the monopolistic nature of a competitive environment in which entrepreneurs face a downward-sloping demand function (see the full-blown model for details).

Type-c projects are financed through optimal contracts with limited enforceability à la Jermann and Quadrini (2010). To finance working capital, entrepreneurs of type-c 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, as the entrepreneur has the ability to default on his obligation. The decision on default arises after the realization of revenues, but before repaying the intra-period loan. If the entrepreneur defaults, the lender can take over the control right of the project and run the project with a survival probability ϕ each period. $\phi < 1$ reflects the fact that only entrepreneurs have the required talent to run their projects efficiently. Define V_{t+1} the value of project to the lender at the beginning of period $t+1$. In particular, the incentive-compatibility condition for a type-c entrepreneur to repay the debt leads to the following financial constraint:

$$D\left(k_t^c\right) \leq \phi\beta V_{t+1} = \sum_{j=0}^{\infty} \left(\phi\beta\right)^{j-1} \pi_{t+j}, \tag{2}$$

where β is the subjective discount factor. π_{t+j} denotes the one-period profit of a project to the lender at period $t+j$. We assume that the lender has unlimited access to external funds and, thus, faces no borrowing constraint. Accordingly, π_t is defined as $\pi_t \equiv \max_{k_t}$ $\left\{Z_t F\left(k_t\right) - \left(r_t + \delta\right) k_t\right\}$, r_t is the rental price of capital and δ is the capital depreciation rate. (2) implies that the entrepreneur can borrow up to the amount that he can pledge to the lender, which is the discounted project value to the lender.

An entrepreneur of a type-c project solves the following problem:

$$\max_{\left\{k_{t+j}^c\right\}_{j=0}^{\infty}} V_t^c = \sum_{j=0}^{\infty} \beta^t \pi_{t+j}^c, \tag{3}$$

subject to (2), where $\pi_t^c \equiv Z_t F\left(k_t^c\right) - \left(r_t + \delta\right) k_t^c$. A combination of the presence of a competitive capital rental market and the entrepreneur's inability to save imply that the current choice of k_t^c depend on neither his previous or future capital rental decisions.

Hence, (3) boils down to a simple repeated one-period problem

$$\max_{k_t^c} Z_t F\left(k_t^c\right) - \left(r_t + \delta\right) k_t^c,$$

subject to (2).

The problem of an entrepreneur of a type-u project is simpler and can be specified as

$$\max_{k_t^u} Z_t F\left(k_t^u\right) - \left(r_t + \delta\right) k_t^u. \tag{4}$$

The first-order condition delivers the standard demand equation for capital, $Z_t F'\left(k_t^u\right) = r_t + \delta$.

Finally, the aggregate output equals to

$$Y_t = \eta Z_t F\left(k_t^c\right) + (1-\eta) Z_t F\left(k_t^u\right) \equiv TFP_t F\left(K_t\right), \tag{5}$$

where $K_t \equiv \eta k_t^c + (1-\eta) k_t^u$ and $TFP_t \equiv \frac{\eta Z_t F(k_t^c) + (1-\eta) Z_t F(k_t^u)}{F(K_t)}$ denote the aggregate capital and TFP, respectively. The marginal effect of a reallocation of capital from the type-u to type-c project on the aggregate TFP follows

$$\frac{\partial TFP_t}{\partial k_t^c} = \frac{\eta Z_t \left(F'\left(k_t^c\right) - F'\left(k_t^u\right)\right)}{F\left(K_t\right)} \tag{6}$$

When the constraint (2) is binding, $F'\left(k_t^c\right) > F'\left(k_t^u\right)$ and such a reallocation would increase the aggregate TFP and, thus, aggregate output. Moreover, the larger is the degree of capital misallocation, captured by the gap of marginal product of capital between these two types of projects, the larger is the magnitude of TFP gain caused by a reallocation of capital to type-c project.

2.2 Household

The representative household maximizes her present discounted life-time utility:

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

subject to the budget constraint:

$$c_t + k_{t+1} = (1 + r_t)\, k_t,$$

where $u'(\cdot) > 0$ and $u''(\cdot) < 0$. Note that in this simple economy, there is no labor and all profits are owned by entrepreneurs. Therefore, rents on capital are the only source of household income. The first-order condition gives the standard Euler equation: $u'(c_t) = \beta u'(c_{t+1})(1 + r_{t+1})$.

2.3 Characterization

To simplify our analysis, we start with situations in which the aggregate technology is a constant. The economy with $Z_t = Z$ for all t will be referred to as regime Z. A permanent change in Z can, thus, be viewed as a regime switch. In the analysis below, we first characterize the equilibrium for a particular regime.[6] We then analyze the dynamics of the economy when it switches from one regime to the other due to variations in Z.

To obtain analytical results, we assume a log preference for the household and an isoelastic function for both production and the working capital requirement. The isoelastic function allows a closed-form solution for the steady-state allocation. Lemma 1 characterizes capital allocation in the steady state. All steady-state values are marked by star.

Lemma 1 *Assume that* $u(\cdot) = \log(\cdot)$, $F(\cdot) = D(\cdot) = (\cdot)^{\alpha}$, *with* $\alpha \in (0, 1)$, *and*

$$\frac{\phi\beta(1-\alpha) Z}{1-\phi\beta} < 1. \tag{7}$$

Then, the financial constraint on the type-c project is binding in the steady state.

See the online Appendix for the proof. The left-hand size of (7) reflects the steady-state capital ratio across the two projects: $(k^{c*}/k^{u*})^{\alpha}$. Clearly, $k^{c*} < k^{u*}$ suggests a binding financial constraint at the steady state.

The following proposition establishes local properties of the recursive equilibrium around the steady state.

[6] A recursive competitive equilibrium for regime Z is defined in the online Appendix.

Proposition 1 *Keep the assumptions in Lemma 1 and further assume that* $\phi\beta \geq 1/2$ *and* $\eta \leq 1/2$*. Then, the recursive equilibrium contains*

(i) A differentiable aggregate law of motion for capital, $\Gamma : R^{+} \times R^{+} \rightarrow R^{+}$*, where*

$$K' = \Gamma(K; Z) = \beta f(K; Z), \tag{8}$$

and $f(K; Z) \equiv (1 + r(K; Z)) K$*;*

(ii) A differentiable value function for the lender, $V : R^{+} \times R^{+} \rightarrow R^{+}$*, where* $V_K(K; Z) > 0$ *and* $V(K; Z_2) > V(K; Z_1), \forall Z_2 > Z_1$*.*

See the online Appendix for the proof. Two remarks are in order. First, (8) implies that K' is proportional to the household's net worth $f(K; Z)$. This comes from two assumptions: log preferences and no labor input. Under these two assumptions, the income and substitution effects of a change in future interest rate cancel each other out. (8) will serve as the key to show analytically the business cycle comovement among output, consumption and investment below. Second, the value function of the lender is increasing in the aggregate capital and technology. This property ensures that the collateral value of the project increases upon the arrival of good news, which relaxes the financial constraint.

2.4 News on Regime Switch

We now consider an anticipated regime switch. Specifically, assume that the economy is in the steady state before period 1, with $Z = Z^{old}$. At the beginning of period 1, the news arrives that the aggregate technology Z will increase to Z^{new} from period 2 onwards, with $Z^{new} > Z^{old}$. Here, the superscripts *old* and *new* on Z denote the original and the new regime, respectively. At period 2, the anticipated permanent technological improvement has materialized. Hence, $Z_t = Z^{old}$ for $t \leq 1$ and $Z_t = Z^{new}$ for $t \geq 2$. We assume that both Z^{old} and Z^{new} satisfy (7).

Before the arrival of the news, the economy is in the regime with $Z = Z^{old}$. After the materialization of the anticipated technological change, the economy switches to a different regime, with $Z = Z^{new}$. The transition from the original regime to the new regime occurs in period 1. The following proposition characterizes how the economy responds to the news on impact.

Proposition 2 *Consider the news described above. Upon impact,*

(i) The future value of the type-c projects increases.

(ii) Capital reallocates from the type-u to type-c projects.

(iii) Aggregate TFP, output and investment increase.

(iv) Aggregate consumption increases if and only if

$$\left(\frac{\phi\beta\left(1-\alpha\right)Z}{1-\phi\beta}\right)^{\frac{\alpha-1}{\alpha}} > 1+\beta\left(1-\alpha\right)\left[1+\frac{\eta}{1-\eta}\left(\frac{\phi\beta\left(1-\alpha\right)Z}{1-\phi\beta}\right)^{\frac{1}{\alpha}}\right]. \tag{9}$$

See Appendix 8.1 for the proof. The intuition is straightforward. The anticipated technological improvement relaxes the financial constraint on the type-c projects by increasing the project value to the lender. The corresponding capital reallocation from the unconstrained to the constrained projects reduces the degree of capital misallocation and, thus, causes aggregate TFP and output to increase. The rise in the current TFP increases the household's net worth and, therefore, causes both the household consumption and aggregate investment to go up, as illustrated by (8).

(9) shows that aggregate consumption increases if and only if capital misallocation at the steady state is sufficiently large. Note that the left-hand side of (9) is the ratio of marginal product of capital, $\left(\frac{k^{c*}}{k^{u*}}\right)^{\alpha-1}$, at the steady state. Condition (9) implies that the larger is steady-state capital misallocation, the larger is the magnitude of TFP gain and aggregate output increase in response to good news, and the more likely the increase in aggregate output dominates the increase in aggregate investment.[7] Note that the comovement upon impact of the news shock will never happen in the standard Real Business Cycle ("RBC" henceforth) models.

3 The Full-Blown Economy

Although the simple model makes the underlying mechanism transparent, it has a number of limitations. First, we do not specify the source of heterogeneity in the working capital requirement. Moreover, the economy is silent on fluctuations in aggregate hours. Third, the productivity dispersion is solely determined by the dispersion in physical productivity, while the empirically measured dispersion in productivity reflects dispersion

[7] (9) implies a large parameter range. For instance, with $\beta = 0.96$, $\alpha = 0.36$ and $\eta = 0.25$, (9) is satisfied with any value of ϕZ between zero and 0.56.

in both physical productivity and prices.

To overcome these limitations, this section extends the simple model in the following aspects. First, we allow all entrepreneurs to save and face the same working capital constraint. As a result, the constraint is binding only for those with insufficient net worth. Second, labor supply becomes endogenous. Third, we adopt product market differentiation to entail price dispersion. Finally, we introduce a stochastic process for the aggregate technology. For quantitative purposes, we also incorporate the following ingredients: a representative capital producer subject to convex investment adjustment cost; trend growth in technology and population; and heterogeneity in production technology across different types of projects.

3.1 Production and Market Structure

Project i, run by entrepreneur i, produces an intermediate good y_t^i, $i \in [0,1]$. The final goods production follows:

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

As will be specified below, the representative household and capital producer use the final goods for consumption and investment. Final good producers behave competitively, while the intermediate good market is monopolistically competitive. Accordingly, the inverse demand function for intermediate good i is $p_t^i = \left(Y_t/y_t^i\right)^{1-\mu}$, where p_t^i is the intermediate good price in units of the final good, and $1/\left(1-\mu\right)$ is the elasticity of substitution. Without loss of generality, we normalize the price of final good to be one.

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

$$y_t^i = \left(A_t^i\right)^{\frac{1}{\mu}} \left(k_t^i\right)^{\alpha} \left(h_t^i\right)^{1-\alpha}, \tag{10}$$

where k_t^i and h_t^i are capital and labor employed in a single project i, respectively. (10) allows technology A_t^i to be different across projects. Specifically, A_t^i contains three components.

$$A_t^i = \left(1+g\right)^t \chi^i Z_t. \tag{11}$$

The first part, $\left(1+g\right)^t$, captures the trend of aggregate technology, where g is the long-run growth rate of aggregate technology. The second and third parts, χ^i and Z_t, respectively, refer to the project-specific technology and detrended aggregate technology. We assume that only the aggregate technology is stochastic. Using the demand function, $p_t^i = (Y_t/y_t^i)^{1-\mu}$, we obtain the revenue function

$$p_t^i y_t^i = Y_t^{1-\mu} A_t^i \left(\left(k_t^i\right)^{\alpha} \left(h_t^i\right)^{1-\alpha} \right)^{\mu}. \tag{12}$$

The curvature in the revenue function originates from the assumption of product market differentiation ($\mu < 1$).

3.2 Entrepreneur Types

Entrepreneurs are classified into two types (type-c and type-u), according to their utility discount factors, with $\beta^c < \beta^u$. In this paper, we focus on the case in which the impatient entrepreneurs are always financially constrained, while the patient ones are not. We then let an entrepreneur with $i \in [0, \eta]$ or $i \in (\eta, 1]$ belong to type-c or type-u entrepreneurs, respectively. For simplicity, we also set production technology A_t^i to be the same for each type of entrepreneurs; i.e., $\chi^i = \chi^c$ for $i \in [0, \eta]$ and $\chi^i = \chi^u$ for $i \in (\eta, 1]$. As a result, the equilibrium outcomes will be the same for projects of the same type. Also, for any variable x, we have $x^i = x^c$ or x^u for $i \in [0, \eta]$ or $i \in [\eta, 1]$, respectively.

3.3 Project Financing

We assume, again, that the magnitude of working capital for a project to be operative increases in the scale of production. An entrepreneur of a type-c project faces the same limited enforcement problem of debt repayment as that in the simple model. Specifically, in case of default, the lender can take over the end-of-period capital owned by the entrepreneur, a_{t+1}^i, and run the project with the type-u technology and a survival probability $\phi < 1$ each period.[8]

Before specifying the collateral constraint for entrepreneurs, it is useful to begin with the project value for the outside lender once default happens. We assume that the outside lender is risk-neutral and has a discount factor of β. Define $\hat{V}$ the value

[8] Later, our calibration results show that $\chi^c > \chi^u$. Therefore, the assumption that the lender can only run the project with the type-u technology captures the fact that, in reality, intangible capital, such as high technology, is difficult to be collateralized.

of project for the lender and $\mathbf{s}_t$ the vector that characterizes the aggregate state of the economy at time t, respectively. Then, $\hat{V}$ has a standard recursive formula:

$$\hat{V}(\mathbf{s}_t) = \max_{\{k_t, h_t\}} p_t y_t - (r_t + \delta) k_t - w_t h_t + \beta \phi E_t \left[\hat{V}(\mathbf{s}_{t+1}) \right], \tag{13}$$

subject to $p_t = (Y_t/y_t)^{1-\mu}$, $y_t = (A_t^u)^{\frac{1}{\mu}} (k_t)^{\alpha} (h_t)^{1-\alpha}$ and a stochastic process of aggregate shocks, which will be specified below.

The borrowing limit of an entrepreneur is set by the value that the lender can recover when the entrepreneur defaults. By selling a_{t+1}^i at period $t+1$ and running the project by herself from period $t+1$ on, the lender can recover $\beta E_t \left[q_{t+1} a_{t+1}^i + \phi \hat{V}(\mathbf{s}_{t+1}) \right]$, where q_{t+1} denotes the capital goods price at time $t+1$ and $\hat{V}(\cdot)$ solves (13). Then, the collateral constraint can be written as

$$D\left(k_t^i\right) \leq \beta E_t \left[q_{t+1} a_{t+1}^i + \phi \hat{V}(\mathbf{s}_{t+1}) \right]. \tag{14}$$

3.4 Entrepreneurs' Decisions

Entrepreneur i makes intra-temporal decisions on factor inputs, k_t^i and h_t^i, and an inter-temporal decision on capital accumulation, $a_{t+1}^i - a_t^i$. The budget constraint is

$$c_t^i + q_t \left(a_{t+1}^i - a_t^i \right) + r_t \left(k_t^i - a_t^i \right) + \delta q_t k_t^i + w_t h_t^i = p_t^i y_t^i, \tag{15}$$

where r_t and w_t are the capital rental price and wage rate, respectively, δ denotes the capital depreciation rate and $p_t^i y_t^i$ follows (12). $k_t^i - a_t^i > 0$ (< 0) implies that the entrepreneur demands (supplies) capital from (to) the rental market.

We assume that entrepreneurs have log utility. Then, their value function solves the following Bellman equation:

$$V\left(a_t^i, \mathbf{s}_t\right) \equiv \max_{\left\{c_t^i, a_{t+1}^i, k_t^i, h_t^i\right\}} \log c_t^i + \beta^i E_t \left[V\left(a_{t+1}^i, \mathbf{s}_{t+1}\right) \right], \tag{16}$$

subject to (14), (15) and $a_{t+1}^i \geq 0$, the non-negative constraint on capital owned by entrepreneur i. The first-order conditions are

$$\frac{1}{c_t^i} = \lambda_t^i, \tag{17}$$

$$\lambda_t^i q_t = \beta^i E_t \left[V_a \left(a_{t+1}^i, \mathbf{s}_{t+1}\right)\right] + \gamma_t^i \beta E_t \left[q_{t+1}\right] + \zeta_t^i, \tag{18}$$

$$MRPK_t^i = r_t + \delta q_t + \frac{\gamma_t^i}{\lambda_t^i} D' \left(k_t^i\right), \tag{19}$$

$$MRPL_t^i = w_t, \tag{20}$$

where λ_t^i, γ_t^i and ζ_t^i are the Lagrange multipliers associated with the budget constraint (15), the collateral constraint (14) and $a_{t+1}^i \geq 0$ respectively. V_x denotes the partial derivative of V to variable x. $MRPK_t^i \equiv \alpha\mu Y_t^{1-\mu} A_t^i \left(k_t^i\right)^{\alpha\mu-1} \left(h_t^i\right)^{(1-\alpha)\mu}$ and $MRPL_t^i \equiv (1-\alpha)\,\mu Y_t^{1-\mu} A_t^i \left(k_t^i\right)^{\alpha\mu} \left(h_t^i\right)^{(1-\alpha)\mu-1}$, representing marginal revenue product of capital and labor, respectively. Finally, the envelop condition is

$$V_a \left(a_{t+1}^i, \mathbf{s}_{t+1}\right) = \lambda_t^i \left(q_t + r_t\right). \tag{21}$$

(19) and (20) pin down the capital and labor allocation across the two types of projects. (20) shows that labor allocation is always efficient. When the collateral constraint is not binding; i.e., $\gamma_t^i = 0$, one can see from (19) that capital allocation would also be the first-best.

Combining (17), (18) and (21), we get

$$\frac{q_t}{c_t^i} = \beta^i E_t \left[\frac{\left(q_{t+1} + r_{t+1}\right)}{c_{t+1}^i}\right] + \gamma_t^i \beta E_t \left[q_{t+1}\right] + \zeta_t^i. \tag{22}$$

When none of the non-negative constraint on a_{t+1}^i and the collateral constraint is binding; i.e., $\zeta_t^i = \gamma_t^i = 0$, (22) reduces to the standard Euler equation with time-varying capital goods prices.

3.5 Productivity Measure and Dispersion

To understand how the collateral constraint affects aggregate TFP through capital allocation, let us first lay out the productivity measures. Following Foster, Haltiwanger and Syverson (2008) and Hsieh and Klenow (2009), we denote $TFPR$ as "revenue productivity," with

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

Note that $TFPR$ is equalized across projects in the first-best. This is because more capital and labor will be allocated to projects with high A_t^i, to the point where the higher output, by lowering the price, yields exactly the same $TFPR$. Moreover, the first-best capital allocation and the dispersion of intermediate-good prices are solely determined by the relative production technology:

$$\frac{k_t^c}{k_t^u} = \left(\frac{A_t^c}{A_t^u}\right)^{\frac{1}{1-\mu}}, \quad \frac{p_t^c}{p_t^u} = \left(\frac{A_t^c}{A_t^u}\right)^{-\frac{1}{\mu}}. \tag{23}$$

When $TFPR$ differs across projects, the ratio of $TFPR$ between two types of projects increases in the ratio of $MRPK$:

$$\frac{TFPR_t^c}{TFPR_t^u} = \left(\frac{MRPK_t^c}{MRPK_t^u}\right)^\alpha. \tag{24}$$

(24) comes from the fact that $TFPR_t^i = \left(MRPK_t^i\right)^\alpha \left(MRPL_t^i\right)^{1-\alpha}$ and $MRPL_t^i$ is always the same across projects.

Two remarks are in order. First, if the collateral constraint is binding only for type-c entrepreneurs; i.e., $\lambda_t^c > 0$ and $\lambda_t^u = 0$, $MRPK_t^c$ will be higher than $MRPK_t^u$ by (19) and k_t^c/k_t^u will be below the first-best level in (23). Accordingly, $TFPR_t^c/TFPR_t^u$ will be above one as indicated by (24). Second, we may also introduce financial frictions on labor allocation by assuming the size of working capital required to increase in h_t^i. Since $TFPR_t^i = \left(MRPK_t^i\right)^\alpha \left(MRPL_t^i\right)^{1-\alpha}$, adding labor misallocation would amplify the effect of variations in financial frictions on the dispersion of $TFPR$ and, thus, strengthen the quantitative results below.[9]

3.6 Capital Allocation and Aggregate TFP

Section 3.5 shows that the degree of frictions on capital allocation can be measured by the ratio of $MRPK$ across two types of projects. With a binding collateral constraint on type-c entrepreneurs, tightening (or relaxing) the constraint will lead to an increase (or

[9] See an earlier version of the paper for details, which is available upon request.

decrease) in the $MRPK$ ratio, which will in turn affect the aggregate TFP by changing capital allocation efficiency.

To see this, let us define the aggregate TFP by "Solow Residual."

$$\log TFP_t \equiv \log \frac{Y_t}{K_t^{\alpha} H_t^{1-\alpha}} = \frac{1}{\mu} \log \left(\begin{array}{c} \eta A_t^c \left(\frac{k_t^c}{K_t}\right)^{\alpha\mu} \left(\frac{h_t^c}{H_t}\right)^{(1-\alpha)\mu} \\ + (1-\eta) A_t^u \left(\frac{k_t^u}{K_t}\right)^{\alpha\mu} \left(\frac{h_t^u}{H_t}\right)^{(1-\alpha)\mu} \end{array} \right). \tag{25}$$

where TFP_t is the aggregate TFP, $K_t \equiv \eta k_t^c + (1-\eta) k_t^u$ and $H_t \equiv \eta h_t^c + (1-\eta) h_t^u$ denote the aggregate capital and labor, respectively. To focus on cyclical changes of the aggregate TFP, we further define $\widehat{TFP}_t \equiv TFP_t / (1+g)^{t/\mu}$ and $\widehat{TFPR}_t^i \equiv TFPR^i / (1+g)^{t/\mu}$, where $(1+g)^{1/\mu}$ is the balanced growth rate of the aggregate TFP. Since $A_t^i = (1+g)^t \chi^i Z_t$, the log change in $\widehat{TFP}_t$ can be decomposed as

$$\triangle \log \widehat{TFP}_t = \underbrace{\frac{1}{\mu} \triangle \log Z_t}_{\text{the technological effect}} + \underbrace{\frac{1}{\mu} \triangle \log \left(\begin{array}{c} \eta \chi^c \left(\frac{k_t^c}{K_t}\right)^{\alpha\mu} \left(\frac{h_t^c}{H_t}\right)^{(1-\alpha)\mu} \\ + (1-\eta) \chi^u \left(\frac{k_t^u}{K_t}\right)^{\alpha\mu} \left(\frac{h_t^u}{H_t}\right)^{(1-\alpha)\mu} \end{array} \right)}_{\text{the reallocation effect}}. \tag{26}$$

The first argument on the right-hand side ("RHS" henceforth) of (26), called "the technological effect," points to the source for aggregate TFP fluctuations through exogenous technological shifts. In standard RBC models, the technological effect, by construction, is the only source for aggregate TFP fluctuations. However, this is not true in the present model. The second argument on the RHS of (26), referred to as "the reallocation effect", captures the effect of changes in the distribution of capital across different types of projects. This becomes an additional source for aggregate TFP fluctuations since a larger $MRPK$ or $TFPR$ dispersion leads to bigger aggregate productive efficiency losses.[10]

[10] Such an effect can be seen from the following expression for the aggregate TFP: $\widehat{TFP}_t = \left(Z_t^{\frac{1}{1-\mu}} \left[\eta \left(\frac{\chi^c}{\widehat{TFPR}_t^c} \right)^{\frac{1}{1-\mu}} + (1-\eta) \left(\frac{\chi^u}{\widehat{TFPR}_t^u} \right)^{\frac{1}{1-\mu}} \right] \right)^{-1}$. This expression shows that the larger is the spread between $\widehat{TFPR}_t^c$ and $\widehat{TFPR}_t^u$, the lower is the level of $\widehat{TFP}_t$. In the first-best allocation, $\widehat{TFPR}_t^i = \widehat{TFP}_t = Z_t^{1/\mu} \left[\eta (\chi^c)^{\frac{1}{1-\mu}} + (1-\eta) (\chi^u)^{\frac{1}{1-\mu}} \right]^{(1-\mu)/\mu}$.

3.7 News Shocks

To isolate the TFP fluctuations originating from the reallocation effect, we would like to introduce certain primitive shocks that trigger capital reallocation but bear no contemporaneous technological effect. Note that any primitive shock affecting the future project value to the lender may serve the purpose. One candidate for such shocks is a news shock on future technology. Specifically, we assume that

$$\log Z_{t+1} = (1-\rho)\log \bar{Z} + \rho \log Z_t + \epsilon_t^Z, \tag{27}$$

where ϵ_t^Z denotes innovations regarding information on the next-period aggregate technology Z_{t+1} and $\bar{Z}$ stands for the steady-state technology. The process (27) is different from the stochastic technology process in standard RBC models. On the one hand, information on Z_{t+1} arrives at time t, before Z_{t+1} is realized. As a result, the next-period aggregate technology becomes perfectly predictable. On the other hand, 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, the news shock leads to variations in financial frictions by changing the project value, as it contains information about future technology. These properties imply that the aggregate TFP fluctuations in response to the news are purely driven by the reallocation effect until the materialization of the technological change.

3.8 Household Sector

There is a stand-in household with N_t working-age members at date t. The size of the household grows over time exogenously at a constant rate $n = N_t/N_{t-1} - 1$. 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

$$C_t + q_{t+1} A_{t+1} = \left(q_t + r_t\right) A_t + w_t H_t + \Pi_t^k,$$

where $c_t \equiv C_t/N_t$ is per member consumption, and $h_t \equiv H_t/N_t$ is the fraction of hours worked per member of the household, $A_t \equiv a_t N_t$ is the total capital owned by the household at the beginning of the period t. Π_t^k is the profit to the capital producer, as will be specified below. The household shares the same discount factor, β, as the outside lender. The first-order conditions imply the following standard equations:

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

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

3.9 The Capital Producer

To pin down the price of physical capital, we assume a representative capital producer following Christiano, Motto and Rostagno (2010). Each period, after the final goods production takes place, the capital producer purchases I_t units of goods from the final good producer and uses these inputs to produce newly installed capital, I_t', by employing the following technology:

$$I_t' = (1 - S(I_t/I_{t-1})) I_t \tag{28}$$

According to (28), the technology of transforming new investment into installed capital for production involves a cost of $S(I_t/I_{t-1})$, with $S'(\cdot) > 0$. As will be shown below, our main results still hold qualitatively with the standard quadratic capital adjustment cost.

After capital goods production, the capital market opens. The capital producer sells the installed capital at a price q_t. Her period-t profit can thus be expressed as

$$\Pi_t^k = q_t (1 - S(I_t/I_{t-1})) I_t - I_t.$$

Dynamically, the capital producer solves the following optimization problem:

$$\max_{I_{t+j}} E_t \left[\sum_{j=0}^{\infty} \beta^j \lambda_{t+j} \Pi_{t+j}^k\right] \tag{29}$$

where λ_t is the multiplier on the household's budget constraint. The first order condition delivers

$$q_t = \frac{1 - E_t \beta \left(\lambda_{t+1}/\lambda_t\right) \left[q_{t+1} S' \left(I_{t+1}/I_t\right) \left(I_{t+1}/I_t\right)^2\right]}{1 - S' \left(I_t/I_{t-1}\right) I_t/I_{t-1} - S \left(I_t/I_{t-1}\right)}.$$

We restrict S to satisfy the following properties: at steady state, $S(\cdot) = S'(\cdot) = 0$ and $\kappa \equiv S''(\cdot) > 0$. Clearly, the steady state of the model does not depend on the adjustment cost parameter, κ. Also, it is easy to see that $\Pi_t^k = 0$ at the steady state.

For a numerical solution, we detrend each per capita variable (except for hours worked) by $(1 + g_y)^t$, where g_y is the growth rate of output per capita on the balanced growth path, with $1 + g_y = (1 + g)^{\frac{1}{(1-\alpha)\mu}}$. The aggregate state vector of the economy, $\mathbf{s}_t$, includes both the exogenous state variables, $\left(Z_t, \epsilon_t^Z\right)$, and the asset distribution among agents, (a_t^c, a_t^u, A_t). We solve for decision rules around the steady state by log-linearizing the necessary equations characterizing the equilibrium and solving for the recursive equilibrium law of motion with the method of undetermined coefficients (Uhlig, 1999).

4 Calibration

In this section, we calibrate the benchmark model using data from the 2011 revision of the National Income and Product Accounts (NIPA) to match the average values of U.S. data over the 1960-2010 period. Our measure of capital stock includes private fixed assets, stock of consumer durables and private inventory. 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. We adopt the GHH as our benchmark preference.

$$u(c_t, h_t) = \frac{\left(c_t - \psi \Pi_t \frac{h_t^{1+\nu}}{1+\nu}\right)^{1-\sigma} - 1}{1-\sigma}, \tag{30}$$

where $\Pi_t = (1+g_y)^t$ is incorporated in the utility to ensure the stationarity of hours on the balanced growth path. There are few empirical studies for the income effect of aggregate labor supply. One exception is the recent work of Schmitt-Grohé and Uribe (2008), who find a near-zero value under a structural Bayesian estimation. In Section 5.3, we will check the robustness of our results under a generalized preference proposed by Jaimovich and Rebelo (2009), which nests as special cases both GHH and KPR preferences.

We set $\sigma = 1$, which corresponds to the case of logarithm utility. ν is set to 0.4 to match a Frisch elasticity of 2.5. The parameter ψ is set to 1.93 so that the hours worked are 0.31 at the steady state. The discount factor β for the household is set to 0.979, implying a steady-state real interest rate of four 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 or over between 1960 and 2010. The discount factor for type-u (patient) entrepreneurs is set equal to that of the household.[11]

4.2 Technology

We let $g_y = 0.0183$, which is consistent with the long-run average growth rate of U.S. real GDP per capita. The price markup over the average cost for an unconstrained project is $1/\mu - 1$. We set $\mu = 0.85$. This implies a markup of 17.6 percent, consistent with Morrison's (1992) empirical evidence. α is set to 1/3.[12] The depreciation rate δ is set to match the average depreciation rate of our measured capital between 1960 and 2010. This gives $\delta = 0.04$. The project survival probability, ϕ, is set to 0.90. Note that ϕ does not affect the steady-state $MRPK$ dispersion once the constrained entrepreneurs are

[11] Notice that when the collateral constraint is not binding for patient entrepreneurs, the steady-state capital owned by a patient entrepreneur, a^u, will be indeterminate. We therefore choose a^u to be sufficiently large to make sure that the collateral constraint is not binding for patient entrepreneurs around the steady state. Our quantitative results are robust to alternative values of a^u.

[12] This implies a capital income share of 0.28 for unconstrained projects if we measure capital income by rents paid to capital owners (i.e., the representative household). The share increases to 0.43 if entrepreneurial profits are also counted as capital income.

allowed to save. In fact, when entrepreneurs are associated with heterogeneous discount factors, the steady-state $MRPK$ dispersion would be solely determined by the dispersion of their discount factors, which is orthogonal to ϕ.

We parameterize the size of working capital as

$$D\left(k_t^i\right) = \Omega_t \left(k_t^i\right)^{\alpha}, \tag{31}$$

where $\Omega_t = (1+g)^{\frac{t}{\mu}}$ is multiplied such that the long-run growth rate of the required working capital is the same as that of revenue. This ensures the collateral constraint to be non-trivial on the balanced growth path.[13] (31) can be motivated by the assumption that working capital required for financing an intermediate input, denoted by m_t^i, is complementary to k_t^i. Specifically, consider an extreme case where the production function takes the Leontief form: $(A_t^i)^{\frac{1}{\mu}} \min\left\{(k_t^i)^{\alpha}, m_t^i\right\}(h_t^i)^{1-\alpha}$. Then, the entrepreneur will always choose $m_t^i = (k_t^i)^{\alpha}$.[14]

Following Christiano, Ilut, Motto and Rostagno (2010), we specify the capital adjustment cost function as $S(I_t/I_{t-1}) = \frac{\kappa}{2}\left(I_t/I_{t-1} - (1+g_y+n)\right)^2$. The literature has various estimates of the adjustment cost parameters, ranging from 2.48 in Christiano, Eichenbaum, and Evans (2005), 2.85 in Primiceri, Justiniano and Tambalotti (2010) to 5.74 in Smets and Wouter (2007). To be conservative, we choose κ such that $S''(\cdot) = 2.5$ at the steady state, which gives $\kappa = 2.5$.

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 0.838 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 (1.38 percent).

We choose η, χ^u, χ^c and β^c to match the following moments. First, we suppose the collateral constraint is binding for the type-c (impatient) entrepreneurs only. This will be confirmed later in the calibrated economy. Hadlock and Pierce (2010) find that the fraction of potentially/likely financially constrained firms ranges from 39.2 percent to 13.2 percent in COMPUSTAT, depending on classification schemes. We therefore set $\eta = 0.25$; i.e., one quarter of the projects in our model are financially constrained. Without loss of generality, we normalize the project-specific technology parameter χ^u to unity.

[13] To check whether our findings are robust to different specifications of $D\left(k_t^i\right)$, we tried a more general setup with $D\left(k_t^i\right) = \Omega_t \left(k_t^i\right)^{\varphi}$, $\varphi \in (0,1]$. Our numerical results below remain qualitatively the same for all values of φ in this range. The robustness check results are available upon request.

[14] See Jermann and Quadrini (2010) for a similar setup.

Since both the aggregate capital-output ratio and the $MRPK$ ratio between the two types of projects are closely related to χ^c and β^c, we calibrate χ^c and β^c simultaneously to match two targets: an aggregate capital-output ratio of 2.9 and an empirical $MRPK$ ratio specified as follows. Hadlock and Pierce (2010) develop a size-age index (SA index henceforth) to measure the likelihood for a COMPUSTAT firm to be financially constrained, with a higher SA index suggestive of a higher probability of being financially constrained. Therefore, we assign COMPUSTAT firms in the top 25 percentiles of the distribution of the size-age index to the financially constrained group, and those in the remaining 75 percentiles to the unconstrained group. Our empirical result in Section 6 implies an average $MRPK$ ratio of 1.44 between 1975 and 2010. Matching the two moments yields $\chi^c = 1.34$ and $\beta^c = 0.745$.[15][16] We find that in this calibrated economy, the collateral constraint is indeed always binding for type-c entrepreneurs around the steady state but has no effect on type-u entrepreneurs.

Table 1 summarizes the calibrated parameter values.

[Insert Table 1]

5 Results

In this section, we first plot impulse responses of macro variables to news shocks on aggregate technology. We then quantify the contribution of our transmission mechanism to aggregate TFP fluctuations. Finally, we conduct robustness checks of alternative model parameterization and specification.

5.1 Impulse Responses to News

The experiment for impulse responses is as follows. The economy is at the steady state in period 0. At the beginning of period 1, all agents receive unanticipated news that Z_t

[15] That more productive type-c projects are financially constrained 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.

[16] Note that at a quarterly frequency, our calibration implies that $\beta_q^c/\beta_q^u = 0.95$, consistent with the corresponding value in the literature (e.g. Carlstrom and Furest, 1997)

will increase by one percent in period 2. At the beginning of period 2, the technological improvement is materialized.

Figure 1 depicts the responses of various variables to the one-percent news shock. We see from Panel A that the ratio of $MRPK$ between the two types of projects decreases by about 0.8 percent on impact. Intuitively, the anticipated technological improvement relaxes the financial constraint on type-c projects by increasing their future values. This causes capital to flow from unconstrained to constrained projects, which reduces the degree of capital misallocation. Moreover, the ratio persistently stays below the steady-state level, suggesting that the variation in financial frictions have persistent effects.

[Insert Figure 1]

The reduction of financial frictions on capital allocation results in an increase in aggregate productive efficiency. This is evident from Panel B, which plots the response of aggregate TFP and its components to the good news. The initial response of TFP amounts to 0.20 percent. The decomposition shows that the reallocation effect explains the entire increase in TFP before the technology improvement materializes. Moreover, since the model generates persistent reallocation effects, TFP fluctuations are amplified when the technological improvement is realized.

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

5.2 Quantifying the Role of Financial Frictions and News Shocks

Our impulse responses suggest that variations in financial frictions on capital allocation not only trigger, but also amplify aggregate TFP fluctuations. What is the quantitative contribution of our proposed mechanism to aggregate TFP fluctuations in the model economy? To address this question, we construct a counterfactual economy in which financial frictions are shut down - i.e., $\Omega_t = 0$ in (31). The standard deviation of innovation σ_ϵ^Z and other parameter values remain unchanged, as in the benchmark case.[17]

[17] The only exception is that we recalibrate $\psi = 2.15$ to target hours worked of 0.31 at the steady state. Our quantitative results below are robust to alternative values of ψ, though.

Figure 2 plots the impulse responses to a new shock in the counterfactual economy. To compare, we also add their counterparts in the benchmark economy, as shown in Figure 1. In the absence of financial frictions, the ratio of $MRPK$ between the two types of project is always equal to one, implying an absence of the reallocation effect. Consequently, when news arrives, aggregate TFP stays the same as in the steady state. The 0.2 percent in aggregate TFP on impact illustrated in Figure 1 can thus be attributed to the presence of financial frictions. Since the demand by entrepreneurs on factor inputs remains unchanged, GHH preferences imply that hours worked and, thus, aggregate output are the same as the steady-state values. Anticipation of future technological improvement leads to an increase in investment. Since aggregate output does not change, consumption has to fall, implying a negative comovement on impact between consumption and investment. In addition to this impact effect, Figure 2 also suggests that financial frictions amplify TFP fluctuations and business cycles after the news is realized. Without financial frictions, the response of all macro variables become significantly dampened due to a dampened response of aggregate TFP, which is driven purely by the technology effects in the counterfactual economy.

[Insert Figure 2]

A comparison of the simulated volatilities of aggregate TFP between the benchmark and counterfactual economy, moreover, should isolate the contribution of variations in financial frictions to the aggregate TFP fluctuations. To compute the standard deviation of aggregate TFP, we simulate both economies 500 times, each containing 50 periods, as our data span 50 years. Then, the simulated aggregate TFP data are H-P filtered with a weight of 100 and the moments are calculated by the frequency-domain method. We find that our proposed mechanism has a sizable effect on aggregate TFP fluctuations. The standard deviation of aggregate TFP drops from 1.38 percent in our model economy to 1.29 percent when financial frictions are shut down. In other words, the presence of financial frictions amplifies aggregate TFP fluctuations by about 0.1 percent.[18]

[18]We view this result as a lower bound for the contribution of financial frictions for the following reasons: (1) The model shuts down the channel through which variations in financial frictions affect the fraction of entrepreneurs, an extensive margin which may potentially reinforce the importance of financial frictions (see Section 5.3 for more details); (2) the productivity dispersion between constrained and unconstrained firms at the steady state is calibrated to match its counterpart in COMPUSTAT data. It is well known that firms in COMPUSTAT, which are publicly listed, is likely to face less binding financial constraint than those non-listed. So, the potential productive efficiency gain would be much larger, should we calibrate our model to match the productivity dispersion in a representative sample. We leave the extension for future research.

To illustrate the role of news shocks in driving capital reallocation, we replace new shocks with the standard unanticipated technological shocks in the model with financial frictions.[19] Interestingly, the on-impact response of the reallocation effect is significantly dampened to 0.14 percent under the unanticipated technological shock (in contrast to 0.20 percent under the news shock). Intuitively, as technological improvement is realized, the demand for capital by unconstrained firms also increases, which pushes up further the interest rate. As a result, less capital is reallocated to constrained firms. This suggests that news shocks are quantitatively more important for capital reallocation than unanticipated technological shocks. Section 6.2 will explore the empirical contribution of news shocks to capital misallocation over business cycle frequencies.

5.3 Sensitivity Analysis

In this section, we first check the robustness of our quantitative results to the share of financially constrained firms. After that, we examine our comovement results under the standard quadratic adjustment cost. Then, a generalized preference proposed by Jaimovich and Rebelo (2009) is adopted to examine our comovement results. Finally, we explore the sensitivity of our results to labor supply elasticity.

The parameterization of η in the benchmark case is chosen to be the average fraction of financially constrained firms in the COMPUSTAT dataset reported by Hadlock and Pierce (2010). 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 to $\eta = 0.132$, the lower bound of the share of financially constrained firms in Hadlock and Pierce (2010).[20] Intuitively, a smaller η weakens the reallocation effect and, hence, dampens the response of aggregate TFP on impact. Quantitatively, the increase in aggregate TFP on impact drops from 0.20 percent in the benchmark case to 0.14 percent with $\eta = 0.132$.[21] Among macro variables, the response of aggregate labor supply on impact drops from 0.28 to 0.19 percent. This is, again, because a smaller η reduces the magnitude of capital reallocation between the two types of projects, which, in turn, depresses the response of wage rate and labor supply. As a result, the increases in consumption and investment become more modest than those in the benchmark case. However, the positive comovement among

[19] Figure A.1 in the Appendix plots the impulse response of the reallocation effect to both types of shocks.

[20] We recalibrate ψ to match the hours worked. All other parameters remain unchanged.

[21] Figure A.2 in the Appendix shows the impulse responses.

macro variables is robust to the much smaller share of financially constrained firms.

Our model assumes fixed shares of different types of projects. Therefore, variations in financial frictions affect capital allocation and aggregate TFP only through the intensive margin. Accumulating evidence, however, suggests that entry/exit significantly contributes to the growth and dispersion of productivity. Since startups and young businesses are particularly vulnerable to financial frictions, adding the entry/exit decision may further strengthen our results via the extensive margin. We find that in a model with endogenous entry, the countercyclicality of financial frictions over business cycles leads to procyclical entry of type-c projects. This channel amplifies and propagates aggregate TFP fluctuations substantially (the details are available upon request).

The presence of convex investment adjustment costs amplifies the impact of news shocks and facilitates the comovement of macro variables. The main channel is through an increase in the expected capital price. Specifically, upon the arrival of good news, an increase in the expected capital price leads to a larger expected capital gain and encourages entrepreneurs to save. This relaxes further the financial constraint and, thus, amplifies the impact effect of news shocks on capital reallocation, aggregate TFP and output. Qualitatively, we find our comovement result to be upheld by the standard quadratic adjustment cost with $S''\left(\frac{I}{K}\right) = 4$ at the steady state, as long as the intertemporal elasticity of substitution is sufficiently large (e.g. $\sigma = 0.3$). In contrast, the comovement between consumption and investment cannot be achieved with quadratic investment adjustment costs in some news-driven business cycle models (e.g. Jaimovich and Rebelo, 2009).

The utility specification in our benchmark model abstracts away the income effect on labor supply. Accordingly, an increase in wage rate due to an increase in labor demand of type-c projects will always lead to an increase in hours worked through the substitution effect. We next check the robustness of the comovement results to alternative preferences with income effect on labor supply. Due to the hump-shaped response of aggregate TFP to news shocks, hours worked may potentially fall on impact if the income effect is sufficiently large. For this reason, the comovement in the benchmark model does not necessarily hold true when the GHH preference is replaced with the KPR preference. The question is, therefore, how small the income effect should be in order to maintain a positive comovement of the macro variables - in particular, hours worked. To address this question, we adopt the preference proposed by Jaimovich and Rebelo (2009):

$$u(c_t, h_t) = \frac{\left(c_t - \psi \frac{h_t^{1+\nu}}{1+\nu} \xi_t\right)^{1-\sigma} - 1}{1-\sigma}, \tag{32}$$

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

$$\xi_t = c_t^{\gamma} \left(\xi_{t-1} \left(1 + g_y\right)\right)^{1-\gamma}, \quad \gamma \in [0, 1].$$

On the one hand, when $\gamma \to 0$, the argument of the period utility function becomes linear in consumption and an isoelastic function of hours worked, which is the GHH preference 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 effect on leisure is stronger.

We search for the maximum value of γ to allow positive comovement of macro variables on impact to news shocks, given our benchmark calibration for all other parameters. We find that as γ increases, the impact response of both hours worked and investment falls. However, even when $\gamma = 1$, aggregate hours worked, investment, consumption and output still respond positively to a new shock on impact.

Finally, it is worth assessing the extent to which the choice of ν or the Frisch elasticity may change our results. To this end, we recalibrate the model such that the Frisch elasticity is 1 or $\nu = 1$.[22] As expected, the response of aggregate labor supply on impact is significantly dampened (dropping from 0.28 to 0.12 percent). This leads to a higher wage rate and a more modest increase in project value. The impact response of aggregate TFP, thus, drops from 0.20 percent to 0.15 percent. The response of aggregate output on impact, accordingly, becomes smaller. This, in turn, dampens the increases in consumption and investment. Yet, our positive comovement of macro variables still survives the much lower Frisch elasticity.[23]

[22] ψ is set to 3.98 simultaneously so that the hours worked is 0.31 at the steady state.

[23] Figure A.3 in the Appendix shows the impulse responses.

6 Empirical Evidence

So far, we have constructed a theory in which financial frictions on capital allocation serve as a transmission mechanism for news shocks to drive aggregate TFP fluctuations. To what extent is our proposed mechanism empirically relevant? Our mechanism delivers two main implications. First, capital productivity dispersion between financially constrained and unconstrained firms is countercyclical. Second, such a measure of capital misallocation responds negatively to news shocks on future technology. The rest of this section uses both firm-level and aggregate data to provide suggestive evidence for these two implications.

6.1 Countercyclical Capital Productivity Dispersion

This section examines the first implication mentioned above: the cyclicality of capital misallocation between constrained and unconstrained firms. Our dataset consists of annual COMPUSTAT data from 1975 to 2010 for publicly listed firms, excluding foreign firms (those with a foreign incorporation code), financial firms (SIC code 6000-6999) and utilities (SIC codes 4000-4949). The details of data sources and construction are in the online Appendix.

6.1.1 Constructing Firm Groups

One of the major difficulties of our empirical analysis is how to distinguish firms that are financially constrained from those that are not. The finance literature provides various approaches to proxy the severity of financial constraints a firm is subject to. However, many of them rely on endogenous financial choices that may not have a straightforward relation to constraints. According to Hadlock and Pierce (2010), two firm characteristics that do appear to be closely related to financial constraints are firm size and age. These classification schemes are in accordance with the conventional wisdom that, in reality, financial constraints become less likely to be binding as young and small firms start to mature and grow.[24]

[24] Hadlock and Pierce (2010) categorize a firm's financial constraint status by carefully reading statements made by managers in SEC filings for a sample of randomly selected firms from 1995 to 2004. They find that their proposed index, based on firm size and age, outperforms other approaches commonly used in the literature, e.g., the Kaplan and Zingales index (Kaplan and Zingales, 1997) and the Whited and Wu index (Whited and Wu, 2006), which rely on endogenous financial choices, such as cash

In light of Hadlock and Pierce's finding, we adopt two approaches as our main classification schemes to sort our sample into financially constrained and unconstrained groups.[25] First, we follow the convention of using firm size as a proxy for financial market access; i.e., smaller firms are more likely to be constrained.[26] In particular, we use one-year lagged book assets (AT) as the sorting variable to rank firms by AT for every year over the 1975-2010 period. The fraction of potentially/likely financially constrained firms in COMPUSTAT, accordingly to Hadlock and Pierce (2010, Table 1), is 26 percent, on average. Therefore, we assign the firms in the bottom quartile of the annual asset distribution to the constrained group, and those in the remaining three quartiles to the unconstrained group.

In the second approach, we use an index constructed by Hadlock and Pierce (2010) as a proxy for the severity of financial constraints, which is referred to as the size-age or SA index. Specifically, they find a nonlinear role of both size and age in predicting the constraint. At certain point, roughly in the sample's ninety-fifth percentile ($4.5 billion in assets, thirty-seven years of age), the relation between the constraint and firm characteristics becomes essentially flat. Below these cutoffs, they uncover a quadratic relation between size and the constraint and a linear relation between age and the constraint.[27] The index is calculated as

$$SA = (-0.737 \cdot Size) + (0.043 \cdot Size^2) - (0.040 \cdot Age), \tag{33}$$

where Size equals the log of inflation-adjusted book assets with Producer Price Index (PPI) as the deflator, and Age is proxied by the number of years since the firm's first year of observation in COMPUSTAT. This index indicates that the severity of financial constraints falls sharply as size and age increase. Eventually, these relations appear to level off. Similar to the first approach, for each of our sample years, we rank firms according to their individual SA index. We then assign firms in the top 25 percentiles of the distribution of the SA index to the financially constrained group, and those in the remaining 75 percentiles to the unconstrained group.

Both approaches need the information of firms' book asset values. After dropping

holdings or leverage.

[25] Later, in Table 3 we show that our main empirical findings below are robust to a broad range of classification schemes commonly used in the literature.

[26] See, for example, Gertler and Gilchrist (1994) and Almeda, Campello and Weisbach (2004).

[27] In calculating this index, Size is Winsorized (i.e., capped) at (the log of) $4.5 billion, and Age is Winsorized at thirty-seven years.

firm-year observations with negative or missing value of book asset, we end up with a sample including $77,750$ observations, with an average of 1944 observations per year. Table A.1 in the online Appendix reports the number of firm-year observations under each of the four financial constraint categories. According to the SA index, for example, there are 23,756 financially constrained firm-years and 71,194 financially unconstrained firm-years. Table A.1 also illustrates the correlation of the two classification schemes. For example, out of the 23,756 firm-years considered constrained according to the SA index, 20,228 are also considered constrained according to firm size, while 3,468 are considered as unconstrained. Similarly, out of the 23,736 firm-years considered constrained according to firm size, 20,288 are also considered constrained according to the SA index. This suggests that most of the small firms in our sample are also relatively young and are classified as financially constrained under both criteria.

6.1.2 Measuring Capital Productivity Dispersion

We now turn to the firm-level productivity measure using COMPUSTAT data. The literature provides various approaches to estimate plant-level $TFPR$ (e.g., Olley and Pakes, 1996 and Levinsohn and Petrin, 2003). These estimations are difficult to apply here since COMPUSTAT does not report firm-specific wage compensation, nor does COMPUSTAT have information on value-added. However, COMPUSTAT contains information on operating income, which corresponds to $py - wh$ in our model.[28] Then, capital productivity (KP henceforth), defined as $KP \equiv (py - wh)/k$, can be measured by the ratio of Operating Income before Depreciation (OIBDP) to one-year-lag net Plant, Property & Equipment (PPENT).[29] We focus on all firm-year observations with positive operating income before depreciation and a non-missing value for capital stock.

We next compute the ratio of capital productivity between the two groups (KP ratio henceforth) as a proxy for the corresponding productivity dispersion caused by financial frictions. Ideally, we should use the $MRPK$ ratio, which is not directly observable. Notice, however, that the $MRPK$ and KP ratios are equal in our model.[30]

[28] In COMPUSTAT, operating income (before depreciation) is equal to sales minus the cost of goods sold and selling, general and administrative expenses. Since value-added can be closely approximately by the sum of labor expenses and operating income (see, e.g., İmrohoroğlu and Tüzel, 2010), we use $py - wh$ to represent operating income.

[29] Similarly, using COMPUSTAT data, Gourio (2007) measures productivity by running a cross-sectional regression of the log of operating income on log capital.

[30] In an earlier version of the paper, we show that even in a model with labor distortions where these two ratios are not equal, the KP ratio can still be a good proxy for the $MRPK$ ratio due to the

6.1.3 Estimating Capital Productivity Dispersion

We then address the empirical strategy of estimating the capital productivity dispersion between financially constrained and unconstrained firms or, more precisely, the relative capital productivity of constrained to unconstrained firms. For each time t, the KP ratio is estimated by regressing log of capital productivity, denoted as $\log KP_{it}$, on a dummy variable, d_{it}, where d_{it} equals one for the constrained firms and zero for the unconstrained.

$$\log KP_{it} = a_t + b_t d_{it} + \varepsilon_{it}. \tag{34}$$

The key coefficient of b_t in (34) corresponds to $\log\left(MRPK_t^c/MRPK_t^u\right)$ in our model, which is expected to have a positive sign. Therefore, the above regression also allows us to test the hypothesis that the constrained firms are more productive than the unconstrained. To reduce the influence of outliers, we Winsorize $\log KP_{it}$ at the first and ninety-ninth percentiles. Our results hold qualitatively without Winsorization. To control for the industry fixed effects on the measured capital productivity gap between the two types of firms, we add industry dummies at the 2-digit SIC level to the above equation.

6.1.4 Results

Table 2 reports the summary statistics of $\exp\left(b_t\right)$, the estimated relative capital productivity of constrained to unconstrained firms. The first four columns report the time-series mean, median, minimum and maximum of $\exp\left(b_t\right)$ between 1975 and 2010. The estimated b_t is statistically significant at one percent throughout the sample years, suggesting that constrained firms are more productive than financially unconstrained firms. As shown by the first two columns, the estimated capital productivity of constrained firms is, on average, more than 30-percent higher than that of unconstrained firms. Notably, the summary statistics under the two sorting schemes are quantitatively similar. This is because most of the small firms in our sample are also relatively young and, therefore, are classified as constrained under both schemes. These findings are robust to

following two properties. First, both ratios are equal to one without financial frictions. Second, the KP ratio is linearly increasing in the $MRPK$ ratio in the presence of financial frictions. Therefore, the model delivers the same implications on the KP ratio as it does on the $MRPK$ ratio: (i) the KP ratio between the two groups is great than one in the presence of financial frictions; (ii) the KP ratio is countercyclical.

different sorting schemes.[31]

[Insert Table 2]

We now provide evidence on the first prediction. The theory implies a countercyclical estimated KP ratio. This can be seen directly from Figure 3, which plots the H-P filtered estimated b_t, using the SA index as the sorting variable. The NBER recessions are highlighted with the shaded bars. The correlation coefficient between the H-P filtered real GDP and the estimated b_t is equal to -0.655. The p-value for testing the hypothesis of no correlation is virtually zero. Using firm size as the sorting variable leads to essentially the same results. More robustness checks can be found in Table 3, which reports the correlation coefficients under a broad range of classification schemes that are commonly used in the literature. Table 3 shows that the correlation coefficients are negative and highly significant under most alternative classification schemes, except for the Kaplan-Zingales index.

[Insert Figure 3 and Table 3]

6.2 The Role of News Shocks to the Measured Capital Misallocation

How important are news shocks as a driving force for observed variations in the capital misallocation between constrained and unconstrained firms (measured by the relative capital productivity)?[32] Apart from news shocks, unanticipated technological shocks may also lead to countercyclical variations in the measured capital misallocation. Therefore, the first step is to identify news shocks. To this end, we use two orthogonalization schemes as proposed by Beaudry and Portier (2006) and extend the identification conditions to a three-variable system, $\mathbf{Y}_t \equiv (TFP, SP, DISP)'$, where SP denotes stock prices and $DISP$ denotes the above measured capital misallocation. All the results

[31] As an additional robustness check, we classify our sample into quartiles of the SA index distribution for each year. We estimate the relative average capital productivity of each corresponding quartile of the SA index to that of the bottom quartile (the unconstrained group) following the approach of (34). We do find the average estimated relative capital productivity monotonically decrease across quartiles (i.e. 1.584, 1.205, 1.075).

[32] We thank the editor for encouraging us to do this exercise.

we report in this section will be based on quarterly data over the period 1975Q2 to 2010Q4.[33] The data source for these three variables is described in the online Appendix.

6.2.1 Identification of News Shocks

Specifically, we consider two alternative moving average representations with orthogonalized errors. The first one imposes an impact restriction on the representation, while the second one imposes a long run restriction. Denote these two alternative representations by

$$\Delta \mathbf{Y}_t = \Gamma(L)\,\boldsymbol{\varepsilon}_t, \tag{35}$$

$$\Delta \mathbf{Y}_t = \widetilde{\Gamma}(L)\,\tilde{\boldsymbol{\varepsilon}}_t, \tag{36}$$

where $\Gamma(L) = \sum_{i=0}^{\infty} \Gamma^i L^i$, $\widetilde{\Gamma}(L) = \sum_{i=0}^{\infty} \widetilde{\Gamma}^i L^i$, $\boldsymbol{\varepsilon}_t \equiv (\varepsilon_{1t}, \varepsilon_{2t}, \varepsilon_{3t})'$ and $\tilde{\boldsymbol{\varepsilon}}_t \equiv (\tilde{\varepsilon}_{1t}, \tilde{\varepsilon}_{2t}, \tilde{\varepsilon}_{3t})'$. The variance covariance matrices of ε_t and $\tilde{\varepsilon}_t$ are identity matrix. The above moving average representations are derived from the estimation of a Vector Autoregression (VAR) in difference for TFP, stock prices and our measured capital misallocation. We estimate VARs in difference for two reasons. First, using augmented Dickey-Fuller and Phillips-Perron tests cannot reject the null of unit root for any of the three variables. Moreover, the Johansen cointegration test fails to reject cointegration rank of 0.[34] We choose to work with five lags, as the Bayesian Information Criteria suggests that five lags are preferable when we test in an ascending way for the optimal number of lags from four quarter to two years.

We next identify a shock that is contemporaneously orthogonal to TFP in (35) and a shock that drives the long run movement of TFP in (36). If these two shocks are extremely highly correlated and lead to similar impulse response functions, following Beaudry and Portier (2006), we will be able to take ε_2 or $\widetilde{\varepsilon}_1$ as news shocks on future technological improvement. Then, we will show how the measured capital misallocation responds to news shocks and to what extent the forecast error variance of $DISP$ can be explained by news shocks.

[33] We choose to work with quarterly data in this section as the length of annual data for the estimated relative capital productivity based on COMPUSTAT is too short for our VAR analysis.

[34] The small sample size, due to the short period of firm assets and other variables that COMPUSTAT has, is another concern. Hamilton (1994) shows that the difference approach improves the small sample performance of all the estimates if the true process is in difference.

The identification conditions are specified as follows. To recuperate the shock that is contemporaneously orthogonal to TFP, we impose an impact restriction that the 1,2 element of the impact matrix in (35) is zero. For the other two restrictions, we let ε_3 have neither on-impact nor long-run effects on TFP. Therefore, ε_3 can potentially capture measurement errors, which is orthogonal to aggregate TFP fluctuations. We allow ε_1 to represent unanticipated technological shocks by imposing no restrictions on it. To obtain the shock that drives long-run movements in TFP in (36), we set the 1,2 and 1,3 elements of the long-run matrix $\widetilde{\Gamma}(1)$ to zero.[35]

6.2.2 Impulse Response of the Measured Capital Misallocation to News Shocks

The impulse responses associated with the shocks ε_2 and $\widetilde{\varepsilon}_1$ are presented in Figure 4. We see that these two shocks induce similar dynamics for all three variables. In Panel A, ε_2 shock, which by construction is an innovation in stock prices and contemporaneously orthogonal to TFP, seems to have a permanent effect on TFP. On the other hand, $\widetilde{\varepsilon}_1$ shock, which by construction affects TFP permanently, has essentially no impact effect on TFP, while it leads to substantial changes in stock prices. These results suggest that ε_2 contains information about future TFP growth and, thus, can be interpreted as news shocks on future technology. The correlation between shocks ε_2 and $\widetilde{\varepsilon}_1$ is 0.93, in line with the findings of Beaudry and Portier (2006).

[Insert Figure 4]

The new findings are that the measured capital misallocation falls sharply in response to both ε_2 and $\widetilde{\varepsilon}_1$ shocks and stay below the initial state persistently, as shown by Panel C of Figure 4. These imply that news on future technological improvement has a persistent negative impact on capital misallocation.[36] To quantify the importance of news shocks to fluctuations in capital misallocation, Panel D plots the shares of forecast error variance of $DISP$ to ε_2 at different horizons. Clearly, both ε_2 and $\widetilde{\varepsilon}_1$, which may entail news about technological innovations, explain a substantial fraction of fluctuations in the measured

[35] We also set the 2,3 element of the long run matrix to zero. However, this additional restriction is imposed to separate $\widetilde{\varepsilon}_2$ and $\widetilde{\varepsilon}_3$ and does not influence $\widetilde{\varepsilon}_1$.

[36] We also estimate the three-variable system using TFP adjusted for capital utilization, as measured by Fernald (2009). The responses of $DISP$ to these shocks are barely affected. The details are available upon request.

capital misallocation at business cycle frequencies. Specifically, under both restrictions news shocks account for about forty (sixty) percent of forecast error variance in the measured capital misallocation four (eight) quarters ahead.

In summary, our empirical evidence suggests that: (1) on average, financially constrained firms are more productive than unconstrained ones in terms of revenue-based capital productivity; (2) the relative capital productivity of the financially constrained to the unconstrained is countercyclical; and (3) news shocks are an important driving force for the countercyclical relative capital productivity. All the evidence is in line with our theory.

7 Conclusion

This paper explores the role of financial frictions on capital allocation in business cycles. We show analytically that variations in financial frictions in response to news about future technology can trigger aggregate TFP fluctuations before the actual technological change is realized. The endogenous fluctuations in TFP, furthermore, lead to a positive comovement among macro variables. When calibrated to the U.S. data, the model economy indicates a quantitatively sizable contribution of financial frictions to aggregate TFP fluctuations. On the empirical ground, using the COMPUSTAT dataset, we find a significant countercyclical pattern for the degree of capital misallocation, which we measure by the relative capital productivity of financially constrained to unconstrained firms. Moreover, our structural VAR analysis reveals that news shock has a significantly negative impact on the measured capital misallocation and can explain a substantial fraction of its fluctuations over business cycle frequencies. Therefore, this paper suggests that from both theoretical and empirical perspectives, financial frictions on capital allocation may serve as an important transmission mechanism of aggregate TFP fluctuations.

We view our work as a first step towards understanding the role of financial frictions on capital allocation in TFP fluctuations over business cycles. The model developed here has abstracted from a number of important issues. For example, an entry and exit decision à la Hopenhayn (1992) can be introduced to explore the effects of financial frictions on aggregate TFP via endogenous changes in the share of firms being financial constrained. A more important issue, perhaps, is individual firm dynamics and its interaction with frictions on capital allocation, on which we are entirely silent. Therefore, it would be interesting to introduce long-term financial contracts in future work. Another important direction is to extend our empirical analysis to the census data. Based on the much more representative sample, we would be able to provide a more accurate quantitative assessment of our theory.

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Table 1. Parameter Values for the Benchmark Economy

Symb.	Definition	Value	Symb.	Definition	Value
	Demographics			Technology	
n	Population growth rate	0.015	α	Capital share	0.33
	Preference		κ	Capital Adjustment Cost	2.5
β	Disc. factor for the household	0.979	g_y	Growth rate of output p.c.	0.018
β^u	Disc. factor for type-u entrepr.	0.979	ϕ	Project Survival Probability	0.90
β^c	Disc. factor for type-c entrepr.	0.745	δ	Depreciation rate for capital	0.04
ψ	Disutility parameter for leisure	1.93	χ^c	Type-c project-specific Tech.	1.34
σ	Relative risk aversion coefficient	1	χ^u	Type-u project-specific Tech.	1
ν	Inverse of Frisch elasticity	0.4	μ	Elasticity of substitution	0.85
	Market		ρ	Autocorrelation coefficient	0.95
η	Fraction of type-c entrepr.	0.25	σ_ϵ^Z	Std. Dev. of News Innovation	0.008

Table 2. Summary Statistics of the Estimated KP Ratio

	mean	median	min	max	std. dev.
SA Index	1.44	1.40	1.15	1.80	0.064
Firm Size	1.36	1.33	1.10	1.71	0.062

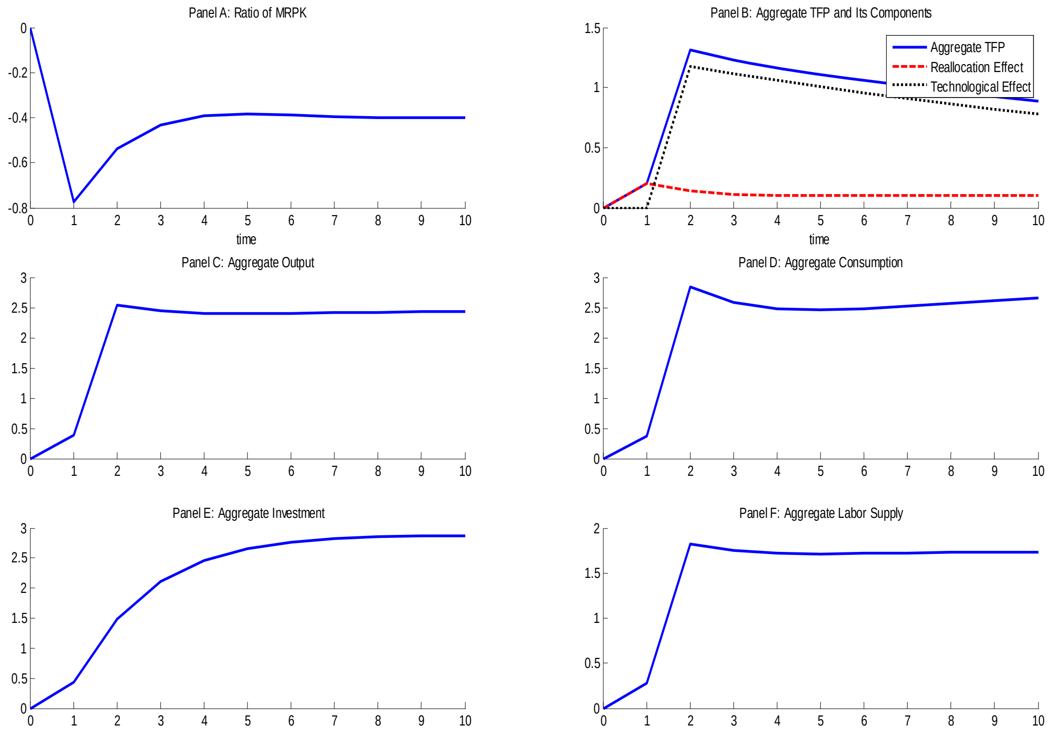
Note: this table provides summary statistics of the estimated KP ratio of constrained to unconstrained firms. SA index and firm size refer to sorting firms by the SA index and one-year lagged book assets, respectively. Each statistics is calculated using time-series of estimated relative capital productivity of constrained to unconstrained firms under the empirical strategies in Section.6.1.3 between 1975 and 2010. The standard deviation in the table is the time-series mean of the standard deviation of estimator between 1975 and 2010.

Table 3. Correlation of the Estimated KP Ratio with Real GDP under Various Classification Schemes

	Correlation with GDP
SA Index	-0.655 (0.0000)
Firm Size	-0.697 (0.0000)
WW Index	-0.533 (0.0008)
Bond Rating	-0.444 (0.0067)
Payout Ratio	-0.412 (0.0125)
KZ index	-0.021 (0.9021)

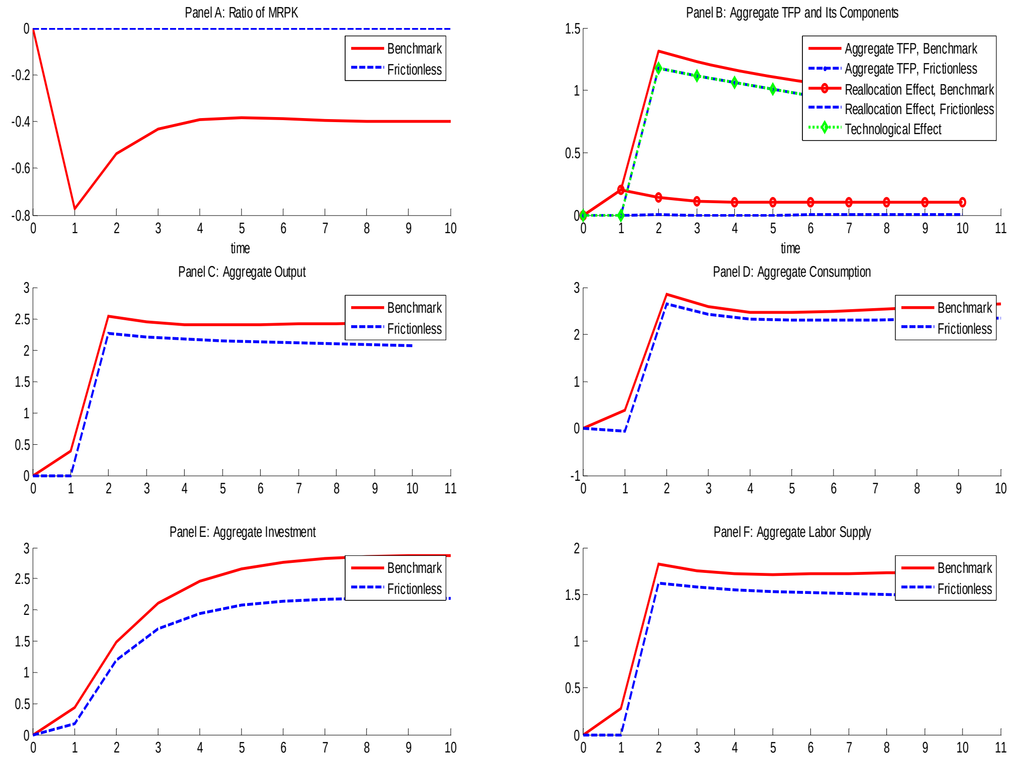
Note: This table presents correlation coefficients between GDP and estimated relative productivity of constrained to constrained firms, both detrended using HP filter. For Size-Age Index, Whited-Wu (2006) index and Kaplan-Zingales (1997) index, firms with financial constraint measures below and above the top 25 percentiles are categorized as unconstrained and constrained; For firm assets, constrained and unconstrained subsamples comprises firms with assets above and below the bottom 25 percentiles. For bond ratings, constrained subsample comprises unrated firms that have positive debt, and unconstrained subsample comprise the rest (including firms with zero debt and no debt rating. For payout ratio, the constrained and unconstrained subsamples comprise firms with payout ratio below and above sample median)). The numbers in the parentheses are the p-values for testing the hypothesis of no correlation.

Figure 1. Impulse Responses to News Shocks on Aggregate Technology in the Benchmark Model



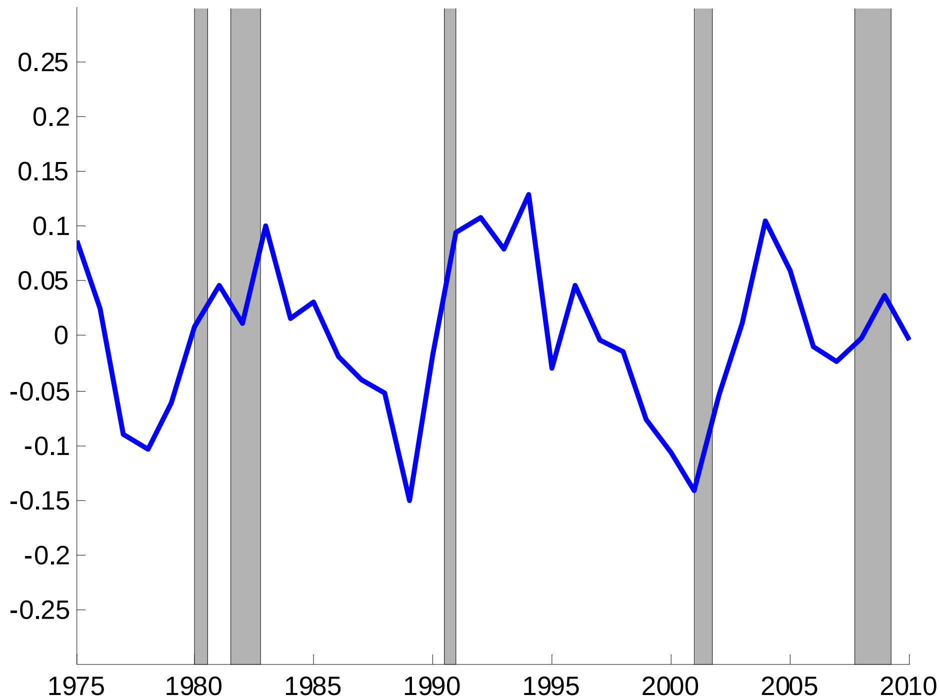
Note: The vertical axes denote percentage deviation from steady state.

Figure 2. Impulse Responses to News Shocks on Aggregate Technology in the Model without Financial Frictions



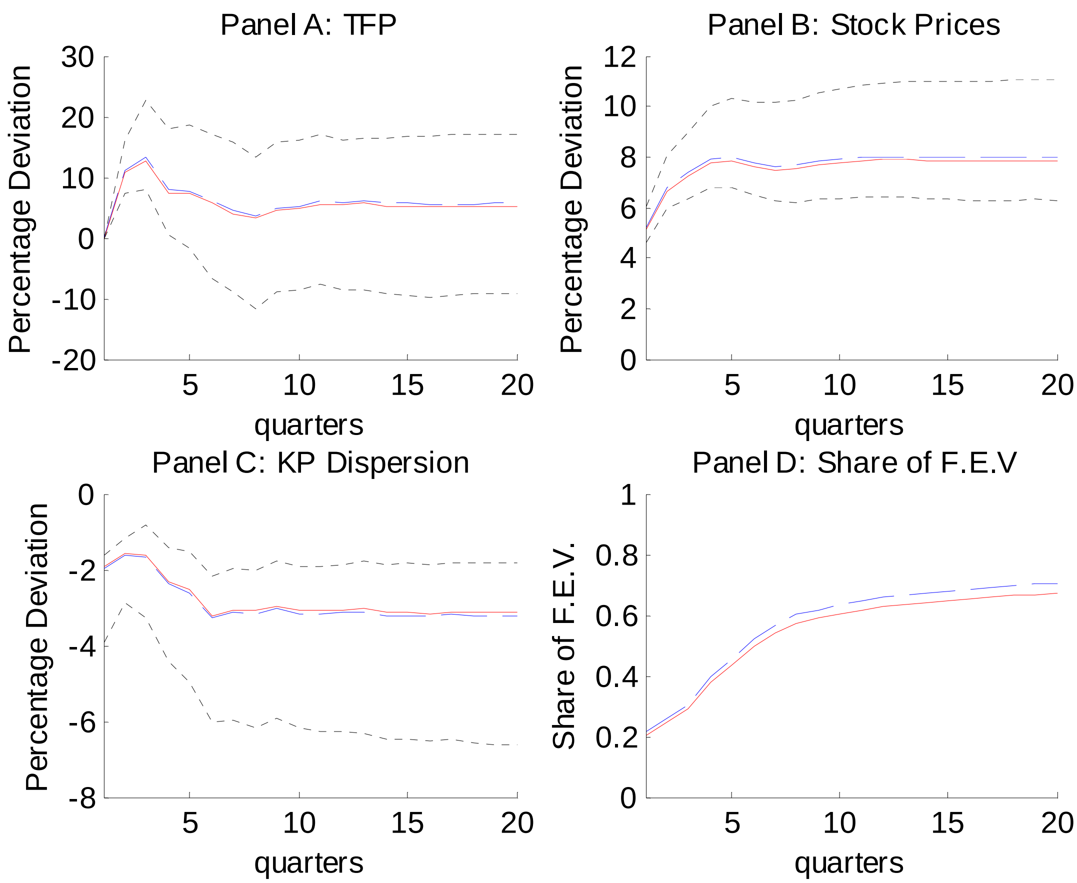
Note: The vertical axes denote percentage deviation from steady state. This figure compares the impulse responses to news shocks under the two economies. The solid lines are the impulse responses in the benchmark economy, while the dash lines are the impulse responses in an economy without financial frictions.

Figure 3. The HP Filtered Estimated Capital Productivity Dispersion over U.S. Business Cycles



Note: The capital productivity dispersion is measured by the estimated b from (34), using the Size-Age index as the sorting scheme. The NBER recessions are highlighted with the shaded bar. See the online Technical Appendix for Data Sources.

Figure 4. Empirical Impulse Responses to Shocks $\tilde{\varepsilon}_1$ andε_2 in the (TFP, SP, DISP) VAR



Note: In Panel A-C of this figure, the bold line represents the point estimate of the responses to a unit ε_2 shock (the shock that does not have instantaneous impact on TFP in the short run restriction). The dash line represents the point estimates of the responses to a unit shock to $\tilde{\varepsilon}_1$ (the shock that has a permanent impact on TFP in the long-run restriction). Both identifications are done in the trivariate system (VAR in difference, five lags). The horizontal axes refer to forecast horizons. The unit of the vertical axis is percentage deviation from the situation without shocks. Dotted lines represent the ± one standard deviation confidence band from 2000 biased-corrected bootstrap replications of the VAR with respect to a unit ε_2 shock. In Panel D, the bold (dash) line represents the share of forecast variance of DISP attributable to shock to ε_2 ($\tilde{\varepsilon}_1$) in the (TFP, SP, DISP) VAR in difference with five lags. The horizontal axes refer to forecast horizons.