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Understanding US Firm Efficiency and its Asset Pricing Implications

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Abstract

We investigate the link between firm-level total factor productivity (TFP) growth, technical efficiency change, and their implications on firm-level stock returns. We estimate total factor productivity growth of US firms between 1966 and 2015 and decompose TFP growth into returns to scale, technical progress, and technical efficiency change components. We show that most of the variation in TFP growth is explained by variation in technical efficiency change. Moreover, we examine the effects of important macro and micro level factors on inefficiency as well as its asset pricing implications. We find that low-efficiency firms are more vulnerable to a wide class of aggregate economic shocks, and the well-known five stock return anomalies (Fama and French, 2015) are more pronounced among those firms. Our results also emphasize the role of macroeconomic determinants of efficiency, and the stability effects of many useful policy targets on firm-level TFP.

Word Count: 12250

Keywords: Asset Prices; Efficiency; Frictions; Stock Return Anomalies; Total Factor Productivity

JEL Classification: D22, D24, G12

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1. Introduction

The failure of maximizing firm's output is pervasive across different firms and industries, and the discrepancy between the actual and the optimal output is the technical efficiency. Many potential reasons are leading to this wedge. For example, managers may have bounded rationality so that their rationality is subject to computational and other constraints, which limits their ability to solve complex problems with precision. Hence, they may make suboptimal decisions (see Simon, 1955, 1957). Even though the managers are fully rational, the presence of technical inefficiency is still possible and may reflect the conflict of interest between firm's managers and owners, as extensively studied in the agency theory literature. Indeed, when the managers are optimally incentivized, they would put high effort towards reaching optimal levels of production given the firm's available resources. However, in practice, it would be difficult to design an optimal scheme to incentivize risk-averse managers. Meanwhile, the financial frictions faced by firms as discussed in a large strand of literature (see e.g., Bernanke, Gertler and Gilchrist, 1999) also limit manager's ability to maximize the output. Under all these views, the sub-optimal resolution to the agency or financing problems leads to sub-optimal productions, i.e., the technical inefficiency.

Our paper contributes to the literature on technical efficiency in many ways. First, by assembling a detailed dataset for US firms (excluding financial and regulated firms), which covers an extended time frame spanning from 1966 to 2015, we show that both technical progress and technical efficiency are important determinants of TFP growth. To this end, we decompose TFP growth into three components.[1] The first component is the returns to scale component, which reflects TFP growth due to deviations from returns to scale. The second component is technical progress, which measures the contribution of technological innovation to TFP growth. The third

[1] We explain this decomposition in Section 2.2. The TFP growth decomposition that we employ is a conventional method and further details can be found in Kumbhakar and Lovell (2003).

component is the technical efficiency change. It turns out that technical progress is relevant as it has the highest percentage contribution to TFP growth, and the technical efficiency change component is important as it has the highest percentage contribution to variation in TFP growth.[2] Some studies in the productivity literature already emphasized the potential importance of technical progress on TFP growth. For example, Fare et al. (1994) use annual GDP data for 17 OECD countries for the 1979-1988 period and show that technical progress is an important determinant of TFP growth, which is in line with our findings. However, to the best of our knowledge, our study is the first to highlight that variation in technical efficiency change may explain most of the variation in TFP growth. Overall, our empirical evidence shows that although the largest portion of TFP growth is due to technical progress, most of the variation in TFP growth is explained by (variation in) technical efficiency change. Hence, technical progress provides a more stable source of TFP growth compared to technical efficiency change, which leads to most of the variation and thus uncertainty in TFP growth. Therefore, it is essential to understand the main drivers of technical efficiency to develop policies that may lead to more stable TFP growth. In particular, to the extent that such policies are feasible and do not involve excessive economic costs to implement, the policies should be aimed at containing the time-varying dynamics of the inefficiency factors. Note that for Yugoslavia, the evidence presented in Nishimizu and Page (1982) contrasts with our results and those in Fare et al. (1994), which indicates the possibility of environments where technical efficiency change may dominate technical progress in terms of explaining TFP growth. Hence, by using a data set that is more extensive compared to many earlier

[2] That is, when we decompose the TFP growth into these three components, the component with highest variance is the technical efficiency change component. This does not necessarily imply that technical efficiency change constitutes a larger portion of TFP growth.

studies (including Fare et al., 1994), we provide further evidence for the importance of technical progress for TFP growth.

Second, we provide an empirical exercise on the macroeconomic and microeconomic factors that affect technical efficiency. For firm-specific environmental variables (i.e., variables that affect efficiency), we find that both the marginal effect of firm age and size are positive, which are reasonably high. We also find that the while macroeconomic factors such as inflation (+), long term interest rate (-), and recessions (-) have all a substantial influence on technical efficiency, credit spread (-) does not have an economically significant effect on technical efficiency. Moreover, we find that technical efficiency displays a statistically significant decreasing trend over our sample period (it ranges from 95.96% (1966) to 87.70% (2015)). The magnitude of efficiency loss over time is striking and shows the importance of understanding the factors that affect inefficiency.

Third, we provide a new perspective on the implications of technical inefficiency by linking technical inefficiency to a firm's stock price. We hypothesize that the technical efficiency proxies for frictions that impede firms from reaching optimal output. Such frictions might go beyond the agency cost (Habib and Ljungqvist, 2005) or the financial frictions (Nguyen and Swanson, 2009). As predicted by many economic models, frictions amplify the fundamental economic shocks (see, e.g., Bernanke and Gertler, 1999; Christiano et al. 2005). Hence, as a testable implication, we should find that stock prices of firms with low technical efficiency are more vulnerable to macroeconomic fluctuations. Specifically, after obtaining firm-level efficiency estimates, we study how stock prices of different firms respond to various macroeconomic shocks conditional on their efficiency levels. Relying on our large panel of US macroeconomic dataset with 101 factors, and a large cross-section of individual stock returns, we find that low technical efficiency firms, or high-frictional firms, are on average more sensitive to fundamental macroeconomic shocks hitting the US economy, including the sector of growth, unemployment, consumption, credit and financial market. Low-efficiency firms are much more vulnerable to macroeconomic fluctuations and quantitatively this effect can be as large as 70% compared to high-efficiency firms. Our rich coverage of economic forces extends the results of Gorodnichenko and Weber (2016), who show that firms with different nominal frictions respond differently to monetary policy shocks. In addition to their focus on the monetary sector, we provide novel evidence that relates firm-level frictions (technical efficiency) to the firm's response to shocks arising from other economic sectors. Note that this is only feasible once we estimate the technical efficiency that can capture the severity of firm-level frictions.

Naturally, our paper is related to the bourgeoning literature that examines the important link between firm-level productivity and asset prices (e.g., Lin, 2012; Imrohoroglu and Tuzel, 2014; Kung and Schmid, 2015). Interestingly, the role of firm-level technical efficiency has largely been ignored within this strand of the literature. Intuitively, it is reasonable to expect that firms with different technical efficiencies would differ in terms of firm's idiosyncratic risk. Among the very few papers related to this line of research, Nguyen and Swanson (2009) find that on average low-operating efficiency firms are more risky compared to those with high-operating efficiency. Our study differs from prior research in several important perspectives. We adopt the technical efficiency measure instead of other efficiency concepts used in the literature, e.g., Habib and Ljungqvist (2005), or Nguyen and Swanson (2009). We then study how the measure for those frictions affect firm's responsiveness to economic shocks and other risk pricing, instead of discussing on whether efficiency itself is a priced risk factor.

As our final contribution, we explore the pricing of four risk factors among firms with different technical efficiency. These four factors, in addition to the market factor, are recently proposed by Fama and French (2015, 2016) to reconcile many existing stock return anomalies. Our view that technical efficiency captures firm-level frictions, which amplify economic risks, naturally motivates this exercise. Indeed, extensive literature documents that the risk premium associated with risk factors are compensations for economic risk (e.g., Petkova, 2006). If low-efficiency firms are more vulnerable to economic shocks, as we have shown above, we then expect that the risk prices will be more prominent among these stocks. We confirm this prediction in the data. The performance of four stock return anomalies, namely the size, value, profitability, and investment, is stronger among low-efficiency firms. For example, the monthly profitability premium among the low-efficiency firms is 0.63% compared to only 0.15% among high-efficiency firms. We further find that such striking difference conditional on the firm-level efficiency also preserves for other stock return anomalies.

The remainder of the paper is organized as follows. Section 2 describes the stochastic frontier model and decomposition of TFP growth. Section 3 describes the data and the estimation results related to the efficiency. In section 4, we examine the asset pricing implications of technical efficiency. Section 5 concludes.

2. Stochastic Frontier Model and Decomposition of TFP Growth

In this section, we provide the details of the model that we use for estimating technical efficiency, and TFP growth and its decomposition. We begin by describing the stochastic frontier model estimation of technical efficiency. Then, we give the technical details for TFP growth decomposition.

2.1. Stochastic Frontier Model: Technical Efficiency Estimation

Traditional economic theory assumes that decision makers can evaluate the actions that enable the firms to reach the highest payoffs. Simon (1955, 1957) argues that the decision makers' computational ability to solve complicated problems is limited, which in turn leads to globally suboptimal decisions. Simon calls this "principle of bounded rationality." In line with this idea, the stochastic frontier models, introduced by Aigner et al. (1977) and Meeusen and van den Broeck (1977), relax the neoclassical full efficiency assumption by treating inefficiency as an unobserved random variable. These models allow us to not only measure the inefficiency but also examine the determinants of inefficiency.

In the production context, the stochastic production frontier models relax the full efficiency assumption by allowing firms to produce suboptimal output levels. In this setting, a firm is technically inefficient if it does not achieve maximum output for given inputs and technology. The conventional stochastic production frontier models (e.g., Battese and Coelli, 1992, 1995; Caudill et al., 1995; and Wang, 2002) assume a composed error term that is the sum of a two-sided error term and a non-negative random variable, which represents inefficiency.[3]

We model the stochastic production function as follows:

$$Y_{it} = F\left(X_{it}, t; \beta\right)\exp\left(-u_{it} + v_{it}\right),$$

where Y_{it} is the output for the productive unit *i*; $F(.)$ is a function representing the deterministic part of the production frontier; X_{it} is a vector of input quantities (X_{nit}) and control variables for the production frontier; $\boldsymbol{t}$ is the time trend; β is a parameter vector; $u_{it} \geq 0$ is a one-sided

[3] For a book-length survey on stochastic frontier models, see Kumbhakar and Lovell (2003).

random variable representing inefficiency; and v_{it} is the usual two-sided error term. When $u_{it} = 0$, the productive unit is assumed to be efficient. The larger values of u_{it} indicate lower efficiency. After taking the logarithm of both sides, we obtain:

$$y_{it} = f\left(X_{it}, t; \beta\right) - u_{it} + v_{it},$$

where $y_{it} = \ln\left(Y_{it}\right)$ and $f\left(.\right) = \ln\left(F\left(.\right)\right)$.

We define technical efficiency (TE) as the ratio of the actual output and the potential output so that $TE_{it} = \exp\left(-u_{it}\right)$. Technical efficiency is identified by using skewness of composed error term $\varepsilon_{it} = -u_{it} + v_{it}$ and can be estimated by:

$$T\hat{E}_{it} = E\left[\exp\left(-u_{it}\right) \mid \hat{\varepsilon}_{it}\right],$$

where $\hat{\varepsilon}_{it}$ is the estimate of ε_{it}.

We assume the following distributions for the random variables that constitute the composed error term, ε_{it}:[4]

$$u_{it} \sim N^{+}(\mu_{it}, \sigma_{it}^{2})$$

$$\mu_{it} = Z_{it}^{'}\delta$$

$$\sigma_{it}^{2} = \exp\left(Z_{it}^{'}\gamma\right)$$

$$v_{it} \sim N(0, \sigma_{v}^{2}),$$

[4] See Wang (2002) for properties of this model. In particular, Wang (2002) emphasizes the potential non-monotonicity of efficiency for this model.

where N^+ is the truncated-normal distribution; and u_{it} and v_{it} are independent conditional on X_{it} and Z_{it}. The parameters of this model can be estimated via the maximum likelihood estimation method. In Section 2.2, we explicitly define the variables that we use in our empirical model and in Section 3 we provide further details about how these variables are used in the estimation.

Finally, note that, in order to differentiate the regressors in the frontier, X_{it}, and the variables that are used in modelling inefficiency, Z_{it}, these variables are given different names in the literature. In particular, the variables in the former group are called “frontier variables” and the ones in the latter group are called “environmental variables.”

2.2. Decomposition of TFP Growth

To estimate TFP growth two approaches are predominantly used. The first approach is the stochastic frontier analysis, which allows the firms to be technically inefficient. The second approach is the variations of Olley and Pakes (1996) and Levinsohn and Petrin (2003), which assumes fully efficiency firms. Hence, we follow the former paradigm to allow technical inefficiency in our model.[5] We define the TFP growth as the difference between output growth and aggregate input growth:

$$T\dot{F}P_{it} = \dot{Y}_{it} - \dot{\Upsilon}_{it},$$

[5] In the neoclassical production context where the inefficiency is not present, it is common to control for potential endogeneity of inputs using variations of methods developed by Olley and Pakes (1996) and Levinsohn and Petrin (2003). Both of these methods assume full efficiency. Hence, they cannot be directly applied to stochastic frontier setting. Moreover, both methods assume that the shock proxy must be monotonically increasing with respect to the true shock. Also, variable inputs (e.g., labor and materials) must respond immediately to a shock while state variables (e.g., capital) must respond after some lag. These assumptions are not necessarily weak and our method does not require them. However, a resulting caveat is that our parameter estimates may suffer from a potential endogeneity problems.

where $T\dot{F}P_{it}$ is the TFP growth; $\dot{Y}_{it} = \frac{d \ln Y_{it}}{dt}$ is the output growth; $\dot{X}_{nit} = \frac{\partial \ln X_{nit}}{\partial t}$ is the growth of input n; and $\dot{\Upsilon}_{it} = \sum_n \frac{e_{nit}}{e_{it}} \dot{X}_{nit}$ is the aggregate input growth, which is defined as a weighted average of input growths; $e_{nit} = \frac{\partial \ln F}{\partial \ln X_{nit}}$ is the output elasticity for X_{nit}; $e_{it} = \sum_n e_{nit}$ is the sum of output elasticities, i.e., returns to scale.

Based on this definition it is possible to calculate TFP growth and decompose it into three components: adjusted returns to scale, technical progress, and growth of technical efficiency. CRS technology has all the growth emanating from technical progress and efficiency change. The decomposition of TFP growth into different components picks up the resulting bias in technical progress when other components are ignored. We decompose TFP growth as follows:[6]

$$T\dot{F}P_{it} = RTSC_{it} + TP_{it} + \Delta TE_{it} ,$$

where $RTSC_{it} = (e_{it} - 1)\dot{\Upsilon}_{it}$ is the returns to scale component; $TP_{it} = \frac{\partial \ln F}{\partial t}$ is the technical progress; and $\Delta TE_{it} = -\frac{du_{it}}{dt}$ is the change in technical efficiency. This decomposition enables us to understand the sources of TFP growth in detail.

We assume that the production function is of translog form with three inputs (labor, capital, and R&D stock) so that:

$$y_{it} = \beta_{ID} + \sum_n \beta_n x_{nit} + \beta_t t + \frac{1}{2} \sum_{n,m} \beta_{nk} x_{nit} x_{mit} + \frac{1}{2} \beta_{tt} t^2 + \sum_n \beta_{nt} x_{nit} t - u_{it} + v_{it} ,$$

[6] See, for example, Kumbhakar and Lovell (2003).

where β_{ID} is the industry dummy variable; and x_{nit} are logarithms of labor quantity ($l = \ln L$), capital ($k = \ln K$), and R&D stock ($r = \ln R$) where $n \in \{l, k, r\}$; and the environmental variables are time trend (t) and its square, age of firm (AGE), logarithm of total assets ($ta = \ln TA$), inflation rate (INF), credit spread (CS), long term interest rate ($LTIR$), and recession dummy *(RecD)*. We impose the usual symmetry restrictions for parameters of a translog model, i.e., $\beta_{nk} = \beta_{kn}$. We predict the components of TFP growth as follows:

$$T\hat{\dot{F}}P_{it} = R\hat{T}SC_{it} + T\hat{P}_{it} + \Delta T\hat{E}_{it} ,$$

where

$$R\hat{T}SC_{it} = \left(\hat{e}_{it} - 1\right) \sum_n \frac{\hat{e}_{nit}}{\hat{e}_{it}} \hat{\dot{X}}_{nit}$$

$$\hat{e}_{nit} = \hat{\beta}_n + \hat{\beta}_{nn} x_{nit} + \hat{\beta}_{nk} x_{kit} + \hat{\beta}_{nr} x_{rit} + \hat{\beta}_{nt} t \text{ for } n \in \{l, k, r\}$$

$$\hat{e}_{it} = \sum_n \hat{e}_{nit}$$

$$T\hat{P}_{it} = \hat{\beta}_t + \hat{\beta}_{tt} t + \hat{\beta}_{lt} x_{lit} + \hat{\beta}_{kt} x_{kit} + \hat{\beta}_{rt} x_{rit}$$

$$\Delta T\hat{E}_{it} = -\Delta E\left[u_{it} \mid \hat{\varepsilon}_{it}\right].$$

3. Estimation Results

We start this section by discussing the data, the estimation of technical efficiency and the links between technical efficiency and firm and market characteristics. Then, we examine the decomposition of TFP growth.

3.1. Data

To estimate the firm-level production function, we include a variety of firm-level variables in our analysis. All the firm-level data are obtained from the Compustat Fundamental Annual file, and we use the data from 1962 to 2015.[7] For each firm, we treat value added, physical capital, and employment as the empirical counterparts to firms' output, capital stock, and labor stock, respectively. The value added is obtained as the Operating Income Before Depreciation and Amortization (Compustat Item 13) plus the labor expenses (product of number of employees and average wage index of the Social Security Administration). On the other hand, the capital stock is given by gross property, plant, and equipment (Item 7), deflated by the price deflator for investment and is constructed following Hall (1990). The labor stock is the number of employees. Finally, as another input of the production function, we construct the R&D stock starting from the data on R&D expenditure and use a widely used method called perpetual inventory method (e.g., Barro and Lee, 1993, 1996; and Hall and Mairesse, 1995) to calculate the R&D stock.

As for the inefficiency part, since our framework enables an explicit incorporation of the fundamentals governing the technical inefficiency, we focus on two classes of variables that enter into the distribution of the efficiency term. The choice of these variables is mainly motivated by their role in characterizing different types of frictions, as we highlight in the introduction that inefficiency can be largely attributed to the presence of these frictions. The first class of variables contains the economy-wide states that could affect the efficiency of all firms. We choose the

[7] Due to the availability of the national average wage index that is required to compute labor input, our sample ranges up to 2015. Following Imrohoroglu and Tuzel (2014), we remove regulated and financial firms from the sample. Also to be included in our analysis, the firms need to have non-missing and positive data on sales, total assets, number of employees, gross property, plant and equipment, depreciation, accumulated depreciation, and capital expenditures.

(aggregate) credit spread *(CS)*, the long-term interest rate (*LTIR*), inflation (*INF*), and the NBER recession dummy *(RecD*) as state (environmental) variables. Credit spreads and long-term interest rates are proxies for external financing, the lack of which may lead to suboptimal financing schemes and therefore inefficient output. Inflation is a gross measure for price stickiness or nominal rigidity, and it has non-trivial effects on the long-term production and sales planning of firms and should be an important state variable for the inefficiency. Last but not the least, firms may act quite differently across business cycles and so are their inefficiencies. In order to capture the aggregate economic regimes, we include a NBER recession dummy variable.

The second class of variables contains firm-specific information that could directly affect inefficiency. Following Hadlock and Pierce (2010), we treat firm size and age as proxies for firm-level financial constraint. The (logarithm of) total assets measures firm size and age is computed as the number of years that the firm is in Compustat with non-missing stock price. Age is winsorized at 37 years to avoid possible dominant effect of firms with long history (see e.g., Hadlock and Pierce 2010). We report the descriptive statistics of both aggregate- and firm-level variables in Table 1.

Table 1. Desciptive Statistics

Variable	Mean	Standard Deviation	5th Percentile	95th Percentile
Y ($M)	1,211.67	4,168.71	6.96	5,700.19
L (K)	14.15	43.42	0.16	67.18
K ($M)	3,684.30	18,587.97	6.32	14,269.94
RD ($M)	635.46	3,067.64	1.19	2,263.84
T	28.00	12.93	8	48
AGE	13.84	10.39	1	37
TA ($M)	5,267.60	24,066.26	20.11	22,127.07
INF (%)	4.07	3.00	0.67	12.10
CS	0.01	0.01	0.00	0.02
LTIR (%)	6.77	2.61	2.43	11.97
RecD	0.14	0.35	0	1
# Observations			61,578	

Note: ($M): Millions of Dollars; (K): Thousands; (%): Percent

3.2. Technical Efficiency, Firm and Market Characteristics

Technical efficiency measures the extent to which a firm maximizes production using a given combination of inputs. The reasons for technical inefficiency include agency costs, mistakes done by managers or other units in the firm, environmental factors such as macro and micro level frictions, etc. In order to measure technical efficiency, we use the stochastic frontier model that we described in Section 2, which measures technical efficiency using the ratio of observed and (unobserved) optimal output levels. In other words, technical efficiency measures the extent to which an output is farther away from the production frontier.

It is possible to treat managerial ability as a proxy for managerial related efficiency (see, e.g., Demerjian et al., 2012). However, there still exist other frictions that can lead to technical inefficiency in addition to the classical agency problem, and estimating only managerial ability does not capture all aspects of efficiency that contribute to TFP. Two related examples for the non-agency related frictions are financial frictions and nominal frictions, which have received considerable attention in the macroeconomics literature (see, e.g. Bernanke et al. 1999, Christiano et al. 2005). Financial frictions represent the imperfect ability of raising external financing, which could lead to shortage of available funding and force managers to cut labor training or equipment maintenance costs that would result in a lower amount of output using the same amount of inputs. Such loss of productivity due the financial frictions yields technical inefficiency. Also, when productivity fluctuates over time, it is well known that due to the costly price adjustment process (i.e., the menu cost), firms may not set optimal prices and wages in response to productivity shocks. For example, when the optimal wage is lower than the current wage, the nominal friction will cause additional costs for firms. Unless firms have enough resources to cover those costs, managers may find it optimal to cut other costs of firms related to capital-specific or labor-specific productivity, similar to the financial frictions' channel.

Hence, for a fully rational economic agent, the occurrence of technical inefficiency may be largely attributed to the existence of agency frictions, financial frictions, or nominal rigidity. Therefore, we advocate that measuring technical efficiency can help shed light on the quantitative magnitude of synthetic US firm-level frictions, which are difficult to quantify empirically. In this paper, we estimate firm-level technical efficiency using our stochastic frontier model on an extensive number of US firms, by explicitly taking into account its potential link with firm's characteristics and macroeconomic factors. Furthermore, we investigate the role of such inefficiency measure in driving TFP growth as well as asset prices. Our study is primarily motivated by Gorodnichenko and Weber (2016), who show that the measurement of costs due to nominal frictions is extremely challenging and therefore rely on stock market data to circumvent that problem. Nevertheless, it remains an unanswered question how to extend their methodology to study other important frictions. In this paper, we confront directly with the measurement of frictions and argue that technical efficiency acts as a natural synthetic metric not only for agency frictions, but also for other types of frictions such as nominal rigidity or financial frictions. Those frictions are well studied in the body of the literature on canonical macroeconomic models (see, e.g., Bernanke et al. 1999; Brunnermeier and Sannikov, 2014), yet with little focus on their empirical estimation. Hence, we contribute to the literature by providing comprehensive firm-level technical efficiency estimates via a stochastic frontier model, and then we associate those estimates, or the synthetic measure for firm-level frictions, with individual stock returns.

In the estimation, we use industry specific dummies to account for industry specific differences so that our technical efficiency estimates are free of industry effects. The production function is assumed to be represented by a translog functional form, which is a second order polynomial approximation of an unknown functional form. The production function estimates are given in Table 2.[8]

The output-weighted averages of returns to scale values range between 0.93-0.96. This indicates decreasing returns to scale though these values are somewhat close to the constant returns to scale level, i.e., 1. The elasticity of output with respect to labor, capital, and R&D stock range between 0.50-0.72, 0.20-0.31, and 0.01-0.13, respectively. While the labor elasticity decreases from 0.72 to 0.52 in the sample time period, R&D stock elasticity increases from 0.01 to 0.13. To illustrate the economic significance our main statistical results, we compare these elasticity values with those of Imrohoroglu and Tuzel (2014). Their production function is a Cobb-Douglas with time-varying parameters and their model has only two inputs, i.e., labor and capital. Moreover, their model does not allow inefficiency so that all firms are assumed to be fully efficient. They find that, in their sample period (1962-2009), labor elasticity range between 0.68-0.76 and capital elasticity range between 0.21-0.31. Hence, while there is some slight discrepancy between our labor elasticity measures and theirs, our capital elasticity estimates are reasonably close. The minor difference in labor elasticity values can be explained by the third input variable (i.e., R&D stock) and the more general production function that we adopt in our estimations.

[8] Since the environmental variables include both micro and macro level variables and the macro variables are not bank-specific, a possible alternative to our model is to introduce a stochastic frontier model that allows such hierarchy. We, however, follow the standard practice in the finance literature and use a conventional stochastic frontier model.

Table 2. Production Frontier Estimation Results

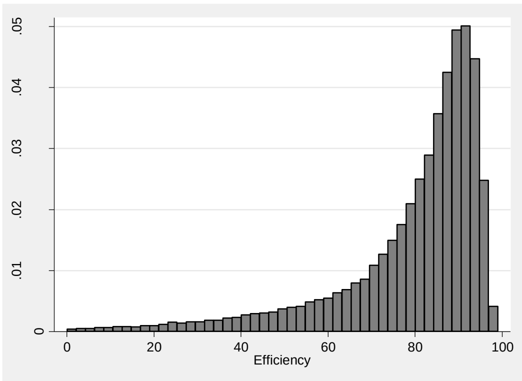
Dependent variable: ln(Y)	**Coef.**		**Std. Err.**
ln(L)	1.3251	***	(0.0124)
ln(K)	-0.3190	***	(0.0103)
ln(RD)	-0.0113		(0.0058)
T	0.0112	***	(0.0008)
0.5 × ln(L)^2	0.1408	***	(0.0044)
0.5 × ln(K)^2	0.1180	***	(0.0027)
0.5 × ln(RD)^2	0.0272	***	(0.0013)
0.5 × T^2	0.0003	***	(0.0000)
ln(L) × ln(K)	-0.1205	***	(0.0030)
ln(L) × ln(RD)	-0.0232	***	(0.0019)
ln(K) × ln(RD)	-0.0013		(0.0014)
ln(L) × T	-0.0002		(0.0002)
ln(K) × T	-0.0010	***	(0.0002)
ln(RD) × T	0.0005	***	(0.0001)
Industry Dummies		YES	
μ			
T	-0.5505	***	(0.0483)
AGE	0.1980	***	(0.0355)
ln(TA)	1.0970	***	(0.1227)
INF	-1.5644	***	(0.1570)
CS	415.0896	***	(67.3189)
LTIR	0.5474	***	(0.1120)
RecD	-1.9263	*	(0.8117)
Constant	1.5239	***	(0.1309)
$\boldsymbol{\sigma_u^2}$			
T	0.0775	***	(0.0022)
AGE	-0.0141	***	(0.0017)
ln(TA)	-0.3611	***	(0.0062)
INF	0.0287	***	(0.0081)
CS	-19.0240	***	(3.4338)
LTIR	0.0288	***	(0.0087)
RecD	0.2345	***	(0.0436)
Constant	1.5239	***	(0.1309)
$\boldsymbol{\sigma_v^2}$			
Constant	-2.6786		(0.0094)
Median Efficiency		85.13	

Mean Efficiency	79.18
# Observations	61,578

Notes: Standard errors are in parentheses. Asterisks indicate significance at the 0.1% (***), 1% (**), and 5% (*) levels.

We compute the firm specific technical efficiencies for each year between 1966 and 2015. The histogram of the estimates is given in Figure 1. The technical efficiency estimates show a statistically significant decreasing trend over the sample period falling from 95.96% in 1966 to 86.70% in 2015. This observation is reflected in the median marginal effect of the time trend variable, which is -0.828, as well. When we do not include environmental variables for the efficiency measure, we still observe a negative trend for technical efficiency.[9] Similarly, returns to scale values decrease from 0.96 to 0.93 but the decrease is less pronounced compared to the efficiency loss over the entire sample time period. Finally, we reject Hicks neutrality at any conventional significance level (p-value = 0.0000).

Figure 1. Technical Efficiency Histogram



Another important question that we address is estimating the (median) marginal effects of environmental variables on technical efficiency.[10] The marginal effect of firm age is 0.066. It is

[9] For the case without environmental variables, we simply regress the technical efficiency estimates on the constant and time trend to test existence and direction of trend.

[10] The marginal effects that we analyze are the median marginal effects.

important to note that the positive sign is consistent with our intuition that the more mature firms handle their operations more effectively and gain efficiency advantage over their rivals. Also, since age is related to the firm' financial constraint, according to Hadlock and Pierce (2010), young firms are more likely to be financially constrained. From this aspect, the age should be positively linked to the technical efficiency. Firm size, measured by total assets, is another relevant factor that turns out to affect technical efficiency positively. In particular, a 1 percent increase in total assets leads to a 0.052 percentage points increase in technical efficiency. While the firm size can potentially impair its operations, Hadlock and Pierce (2010) argue that larger firms actually face lower funding constraints. They find that the severity of financial constraints of firms decrease with firm size. Moreover, the executive managers of larger firms may face relatively more pressure from the shareholders and are likely to have higher remunerations, which would force and incentivize them to work harder to achieve higher efficiency levels. Given the above potential reasons, it is not surprising that our results show a positive marginal effect for the firm size.

When we evaluate the effect of aggregate variables on efficiency, it turns out that the marginal effect of inflation on technical efficiency is 0.867. The median of the absolute value of the yearly change in inflation is 1.303. Hence, inflation leads to a non-negligible and positive variation of technical efficiency. Notably, this result is consistent with a large strand of the macroeconomics literature on the inflation-growth nexus (see, e.g., a review by Espinoza et al., 2010). Since our study focuses on US firms, a positive link between inflation and economic growth is consistent with several features of inflation and growth dynamics documented in the extant literature. The economic basis for this interpretation is the premise that a higher inflation suggests improved economy prospects. Therefore, forward-looking firms will likely internalize this in their operations strengthening their efficiency. Moreover, we can see from our estimates (see Table 2) that various aggregate variables that negatively affect firm's financing conditions have a consistently negative effect on technical efficiency. The marginal effect of credit spread is -11.727. The median of the absolute value of the annual change in credit spread is 0.0036. Hence, overall credit spread does not seem to lead to much variation in technical efficiency. Similarly, the long-term interest rate's marginal effect on efficiency is -1.028. Higher aggregate credit spread or long-term interest rate increase the funding cost for all firms. The median of absolute value of yearly change in long-term interest rate is 0.84. Hence, we predict an annual 0.86 percentage points technical efficiency change solely due to changes in long-term interest rates. We should note that while the magnitude of the effect of long-term interest rate on technical efficiency is smaller than the inflation rate, it is still an important factor that contributes to efficiency. Finally, as expected, recessions do affect technical efficiency substantially. In particular, the median marginal effect of a recession on technical efficiency is -2.269. The 10 percentile of this marginal effect is -5.716. Therefore, a recession (holding other factors constant) can have substantial implications for firm's technical efficiency.

Importantly, the state variables for policy makers also turn out to be important drivers of efficiency and hence TFP growth. For example, we add considerable evidence for the importance of price stability (and stable long-term interest rates) for TFP growth. Therefore, this evidence provides strong support for our approach emphasizing the role of macroeconomic determinants of efficiency, and the stability effects of many useful policy targets on firm-level TFP.

3.3. TFP Growth

TFP is an overall measure of how effectively the inputs are used in a production process, which we define as the ratio of output and the amount of inputs used in the production process.

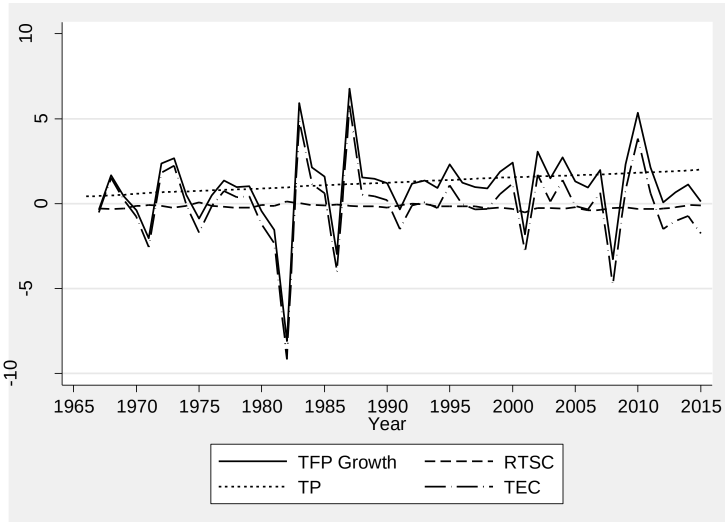
Hence, TFP growth accounts for effects in output growth relative to input growth. We decompose TFP growth into three components. The first component is the returns to scale component, which we measure by a (input-growth weighted) deviations from constant returns to scale. Hence, when the firm exhibit constant returns to scale, this component vanishes. The second component is the technical (technological) progress, which is a measure of improvement in the state of technology. The third component is the change in technical efficiency, which reflects changes in suboptimal production in the sense that the production is farther away from the production frontier.

In Table 3 and Figure 2, we present the output-weighted averages of this decomposition along with the technical efficiency estimates over time. As it can be seen, the returns to scale effect on TFP growth is much more weaker than technical progress and technical efficiency changes effects. While most of TFP growth is due to technical progress, 93.8% of the variation in TFP growth is explained by technical efficiency change. Therefore, even though technical progress is an important determinant of TFP growth, its variation is relatively small and does not contribute to the variation of TFP growth as much as technical efficiency change does. Furthermore, our results remain robust even to the exclusion of the environmental variables in the efficiency estimations. This finding clearly reveals the importance of gauging a better understanding of the key determinants of technical efficiency. The years 1981-1982 (1981 crisis), 1986 (oil price crisis), 2001 (September 11 event), and 2008-2009 (2008-2009 financial crisis) represent critical periods when TFP growth declines dramatically. Hence, our TFP growth estimates are consistent with these major events.

Table 3. TFP Growth, Its Decomposition, and Technical Efficiency Estimates

Year	TFPG	RTSC	TP	TEC	TE
1966			0.43		95.96
1967	-0.35	-0.29	0.45	-0.51	95.48
1968	1.67	-0.32	0.48	1.51	96.83
1969	0.43	-0.30	0.52	0.22	96.96
1970	-0.39	-0.15	0.59	-0.78	96.07
1971	-2.03	-0.09	0.64	-2.55	93.78
1972	2.36	-0.13	0.67	1.83	95.22
1973	2.68	-0.24	0.70	2.23	97.20
1974	0.52	-0.13	0.72	-0.07	97.17
1975	-0.88	0.07	0.75	-1.70	95.56
1976	0.50	-0.13	0.78	-0.16	95.35
1977	1.36	-0.19	0.81	0.74	96.10
1978	0.97	-0.25	0.84	0.39	96.46
1979	1.04	-0.25	0.86	0.43	96.92
1980	-0.43	-0.08	0.89	-1.24	95.83
1981	-1.56	-0.14	0.92	-2.33	93.65
1982	-8.08	0.13	0.96	-9.17	86.47
1983	5.92	0.02	1.02	4.89	90.92
1984	2.14	-0.09	1.06	1.17	91.64
1985	1.59	-0.10	1.08	0.61	92.33
1986	-2.97	-0.06	1.12	-4.03	88.82
1987	6.77	-0.13	1.15	5.75	93.47
1988	1.55	-0.16	1.18	0.53	93.94
1989	1.47	-0.16	1.20	0.43	94.31
1990	1.19	-0.23	1.22	0.20	94.43
1991	-0.35	-0.10	1.26	-1.51	93.00
1992	1.18	0.00	1.29	-0.11	92.78
1993	1.37	-0.03	1.33	0.07	92.76
1994	0.93	-0.17	1.36	-0.26	92.39
1995	2.30	-0.17	1.39	1.08	93.20
1996	1.23	-0.16	1.42	-0.03	93.06
1997	0.98	-0.16	1.47	-0.33	92.62
1998	0.90	-0.30	1.50	-0.30	92.20
1999	1.87	-0.22	1.53	0.56	92.55
2000	2.41	-0.32	1.56	1.18	93.17
2001	-1.81	-0.52	1.57	-2.87	90.72
2002	3.05	-0.25	1.60	1.70	91.73
2003	1.50	-0.26	1.62	0.13	91.65
2004	2.71	-0.31	1.64	1.37	92.30
2005	1.32	-0.22	1.67	-0.14	92.07
2006	0.94	-0.40	1.69	-0.35	91.82
2007	1.97	-0.37	1.72	0.63	92.36
2008	-3.26	-0.26	1.75	-4.75	88.55
2009	2.31	-0.22	1.79	0.74	88.73
2010	5.35	-0.30	1.82	3.84	90.44
2011	2.14	-0.32	1.85	0.61	91.03
2012	0.08	-0.30	1.88	-1.50	89.84
2013	0.66	-0.22	1.91	-1.02	88.76
2014	1.13	-0.09	1.95	-0.73	87.96
2015	0.14	-0.10	2.00	-1.76	86.70

Figure 2. TFP Growth and Its Decomposition



4. Asset Pricing Implications of Technical Efficiency

4.1 Efficiency and Firm-Level Macro Sensitivity

We have shown in the previous sections that firm's technical efficiency is clearly affected by both macroeconomic and firm-specific factors. Moreover, we have provided compelling evidence that technical efficiency change explains much of the variation in TFP growth. The important role of efficiency in determining firm’s productivity and in reflecting firm-level frictions motivates a closely related yet largely unexplored question so far in the literature: what is the role played by efficiency in transmitting economic shocks? The motivation for analyzing this problem is natural in our framework. As discussed earlier, the firms’ ability of maximizing the output given the inputs depends crucially on a variety of frictions. There exist many articles that document the importance of firm-level frictions for amplifying macroeconomic shocks, especially from the theoretical perspective (see, e.g., Bernanke and Gertler, 1999, Gilchrist et al. 2014). Nevertheless, empirical attempts towards quantifying the effects of those frictions remain somewhat scarce in the literature. Therefore, we explore whether our technical efficiency measures are related to the firm's sensitivity to macroeconomic shocks.

We first estimate firm's sensitivity to macroeconomic shocks using a firm's stock return as the response variable to macroeconomic shocks. Our estimates of macro sensitivity based on stock market data is consistent with a recent study by Gorodnichenko and Weber (2016), who use intraday data from the stock market to track the cost of nominal rigidity. Compared with the data of firms' fundamentals, which is only available at the quarterly or annual frequency and often subject to large measurement errors, stock return data is available at higher frequency and is more accurately measured. The reliability of the data is crucial for obtaining a good measure for how individual firms respond to macro shocks.

To keep the analysis as comprehensive as possible, we consider all individual firms with available return and technical efficiency estimate and a large (balanced) panel of monthly US macro dataset that consists of 101 variables recently built by the Federal Reserve Economic Data (FRED).[11] To start with, we obtain the macroeconomic shocks as the innovations from an estimated AR(1) model for each of the economic variables.[12] Then, we measure the macro sensitivity of firm i to the shocks to j-th macroeconomic variable X_{jt} by estimating the following equation:

$$r_{it} = \alpha_{ij} + \beta_{ij} X_{jt} + \gamma_{ij} MKT_t + \delta_{ij} HML_t + \eta_{ij} SMB_t + \varepsilon_{ijt},$$

where r_{it} is the month t stock excess return of firm i, and we control for the Fama-French three factors,[13] that is, the market return (MKT), the size factor (SMB), and the value factor (HML) in

[11] See https://research.stlouisfed.org/econ/mccracken/fred-databases/

[12] We transform the raw data according to the transformation code of each variable provided in the FRED database before extracting the macro shocks.

[13] The data for the factors is obtained from Kenneth French's website.

the regression when estimating the macro sensitivity β_{ij}.[14] The regression is estimated at the end of each month via an expanding-window using the weighted-least-square (WLS) estimation, where we use all previous historical data of returns and factors but assign more important weights to recent observations. Such method is similar to the conventionally used rolling regressions yet has the advantage of using all available historical data instead of the fixed window size. Hence, the WLS method may deliver statistically more efficient estimates for the parameters in a setting of sequential estimation[15] We use the absolute value of β_{ij} as firm i's sensitivity to macro variable j in our subsequent analysis.[16]

Then, to explore the role of firm-level technical efficiency, after obtaining the macro sensitivities for each firm, we evaluate how low- and high-efficiency firms differ in terms of such macro sensitivity via the portfolio sorting method, which is standard in the empirical finance literature (see e.g., Fama and French, 1993). More specifically, at the end of each year, we sort on firms' technical efficiency estimates obtained from our previous section, and attribute these firms' stocks into one of the portfolios. By construction, the sorted portfolios only differ in terms of the technical efficiency of constituting stocks during the past year. We then investigate whether there is significant difference in the macro sensitivity of these portfolios, which enables us to evaluate the cross-sectional relation between firm's macro sensitivity and its technical efficiency. It should be noted that in contrast to the conventional linear regression approach by regressing time-varying macro sensitivity on firm-level efficiency, sorting stocks into portfolios based on technical efficiency and evaluating the cross-sectional differences of those portfolios' macro sensitivities

[14] Our results are quantitatively similar using different controls, such as only including the market factor.
[15] We use the exponential decaying weights, with the half-life of weights to be around 60 months. Again, the results are robust under the alternative decaying rate.
[16] See also the discussions in Gorodnichenko and Weber (2016) and Hong and Sraer (2016).

does not require any parametric assumptions. This is especially important since even though we argue that the technical efficiency score summarizes the information of various frictions, the amplification effect or macro sensitivity resulting from those frictions may be highly nonlinear, as clearly documented in recent theoretical investigations (see, e.g., Brunnermeier and Sannikov, 2014).

To build our portfolios, at the end of each month, we form five portfolios by sorting all firms according to their technical efficiencies for the last fiscal year-end. Moreover, to avoid possible distortive effects of other firms' characteristics, we use the technical efficiency score estimated unconditionally on aggregate and firm-level variables.[17] Then, we compute the equal-weighted and value-weighted average of absolute macro betas of stocks within each portfolio, and for each macroeconomic shock. The results by using different weighting schemes are important. As pointed out by Avramov et al. (2013), equal or value-weighted portfolios may be dominated by either small stocks or large stocks. Focusing on either instead of both cases may give an incomplete picture on the importance of efficiency. In Panel A and Panel B of Figure 3, we plot the proportional difference between average absolute betas of portfolio 5 (high technical efficiency) and portfolio 1 (low technical efficiency) for all macro factors, when portfolios are equal- or value-weighted.

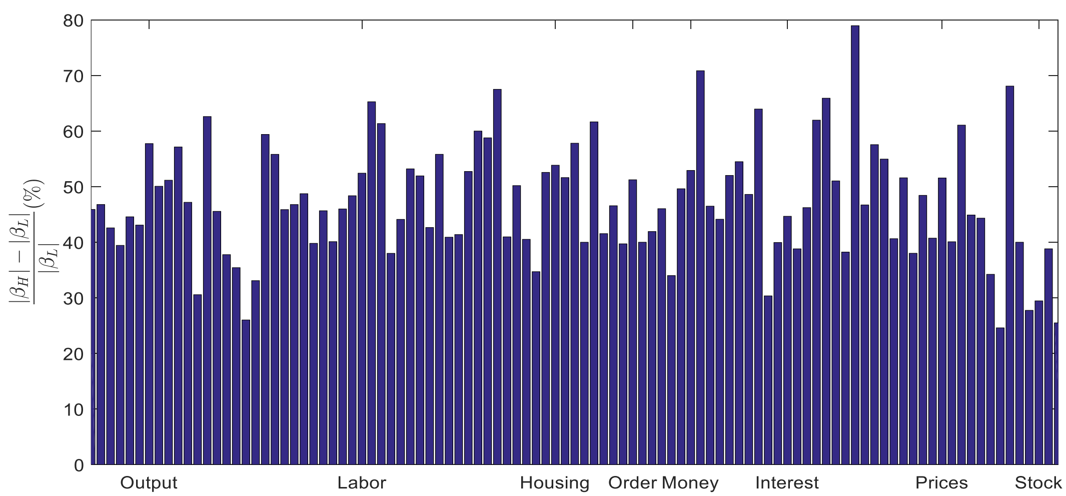
A striking pattern that emerges from Figure 3 is that the portfolio with the lowest technical efficiency is unambiguously more sensitive to macroeconomic shocks in output, labor market, housing, consumption, credit, interest or exchange rate, inflation, and the aggregate stock market.[18] For the value-weighted scheme, on average the portfolio with the lowest technical efficiency is

[17] Our results are of similar or even stronger magnitude if we use the estimated efficiency measure discussed in the previous sections.
[18] We only report the results for the highest and lowest efficiency-sorted portfolio. For most of macro factors considered, the sorted portfolios show monotonically decreasing sensitivities from low- to high-efficiency portfolios.

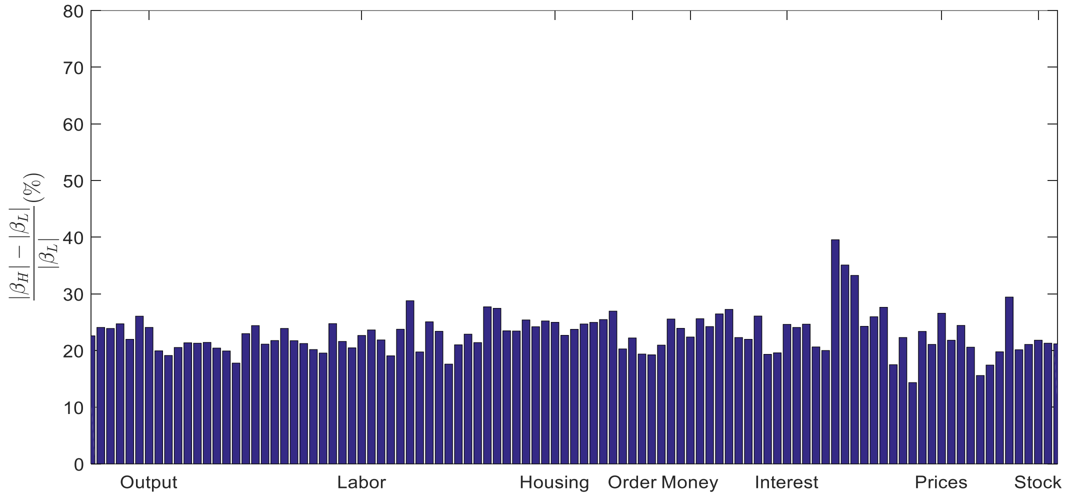
40% more sensitive compared with the highest efficiency portfolio. Moreover, the ratio is relatively stable across different economic sectors, suggesting that our efficiency measure indeed captures firm characteristics and serves as a good synthesis of the frictions. Interestingly, the differential response to aggregate stock market fluctuations is among the lowest especially if compared with the response to macroeconomic shocks. Hence, this result avoids the concern that our sensitivity measure estimated solely from stock market data will mechanically lead to a larger response to financial market fluctuations. In other words, even though we do not rely on firm's fundamental data (which is only available at lower frequency and typically subject to serious measurement errors) when estimating the response to macroeconomic shocks, our evidence suggests that the asset price based method can still effectively capture macroeconomic sensitivity, instead of only financial market conditions.

Figure 3: Macro Sensitivity and Efficiency-Sorted Portfolios

Panel A: Value-Weighted Portfolios



Panel B: Equal-Weighted Portfolios



Further results on the equal-weighted scheme confirm our findings, though the proportional differences now drop to around 20% for many macro factors, and the distribution across economic variables is even more stable compared with that of the value-weighted scheme. Hence, our results are unlikely to be driven by neither small- nor large-size firms because we observe similar patterns across these two distinct groups. Concurrently, one theme of our analysis is to show that both weighting schemes deliver similar results not only in terms of general pattern across all macro variables considered (as shown in Figure 3), but also for each individual macroeconomic factors. Hence, we first rank the proportional differences of sensitivities to 101 macroeconomic factors for both equal- and value-weighted schemes. Then, we regress the sorted indices on a set of macroeconomic factors under the value-weighted scheme on those under equal-weighted scheme. The slope coefficient is 0.78 (note that a perfect alignment of two schemes will give a value of 1) and is statistically highly significant. Therefore, the sensitivity difference is similar even for individual specific macroeconomic factors, under different weighting methods. The useful information contained in the cross-section of technical efficiency indeed help gauge how each firm is likely to respond to macroeconomic shocks. Note that the strong result is based on the limited information we use to estimate technical efficiency. This arguably highlights the importance of technical efficiency, not only for firms' owners, but also for industry and policymaker stakeholders.

4.2 Implications for Stock Return Anomalies

We have provided ample evidence that high technical efficiency firms are less prone to macroeconomic shocks compared with low technical efficiency firms. A natural consequence is that the pricing of risk, which essentially reflects the compensation for economic risk, should be more pronounced among low efficiency firms. In this subsection, we confront with this important exercise that links our paper to the extensive research on stock return anomalies. A large strand of the literature documents the failure of the classic CAPM model, and influential papers such as Fama and French (1993) and Fama and French (2015) propose new factors to better capture the cross-section of stock returns. The common rationale is that those new factors are proxies for economic risk that goes beyond the market risk. Indeed as shown by Fama and French (2016), their newly proposed four factors (SMB, HML, RMW, CMA) go a long way towards resolving various well-known cross-sectional stock return anomalies that cannot be explained by CAPM. Since we hypothesize that inefficiency reflects firm-level frictions that prevent firms from reaching optimal production, it naturally serves as an important risk source and may differ from the CAPM. In particular, we should find that the failure of CAPM is more severe among low efficiency firms, that is, the Fama -French factors should perform better. Hence, in this section we focus on the risk pricing associated with these four factors, i.e., the differences of risk premia related to the size, value, profitability, and investment anomalies between stocks of high- and low-efficiency firms.

It is worth mentioning that the primary focus of our investigation here is on the interaction between well-known risk premium anomalies and technical efficiency, instead of the pricing of efficiency itself (see, e.g. Nguyen and Swensen, 2009). Therefore, even though firms with high or low efficiency may have quite different return profiles, it is far from obvious how efficiency relates to other risk sources that the four well-known anomalies subsume. Examining the multi-dimensions nature of the risk-return relation as emphasized by Cochrane (2011), we contribute to this literature by providing the first formal analysis of the relations of technical efficiency with well-known stock market risk premium anomalies.

Next, we re-employ the portfolio sorting approach outlined in the previous subsection. At the end of each month, we form 5 portfolios sorted by one of the four characteristics mentioned above.[19] We then sort all stocks within each portfolio into 2 sub-portfolios based on their technical efficiency level of the last fiscal year end. Each portfolio is rebalanced monthly and we document the realized excess returns in the following month associated with each portfolio. Table 4 displays the results for value-weighted portfolios.

One notable common pattern from the results is that for all double-sorted portfolios, the average portfolio excess returns are higher among portfolios for low-efficiency firms, given any specific characteristics. This result is consistent with Nguyen and Swensen (2009), who find that the low-efficiency firms are risky. However, our new insight here is that with respect to the differential risk pricing between portfolios for high- and low-efficiency firms, we find that the risk premia (absolute value of the return spread between high and low characteristic-sorted portfolios) for three out of four characteristics are all higher. The most prominent difference is for the profitability premium, with the monthly excess return is 0.62% (t-statistic equals to 2.89), while those for high efficiency stocks are only 0.16% and 0.95 respectively.

[19] Following the standard approach in the literature, we match accounting data for fiscal year-ends in calendar year t-1 to monthly returns from July t to June t+1.

Table 4. Stock Return Anomalies and Productive Efficiency (Value-Weighted)

	Low Efficiency						High Efficiency					
	L	2	3	4	H	HML	L	2	3	4	H	HML
Size	1.65	1.39	1.27	1.29	1.06	-0.59	1.38	1.23	1.25	1.14	0.91	-0.47
	(4.61)	(4.20)	(4.13)	(4.71)	(5.29)	(2.11)	(4.39)	(3.95)	(4.25)	(4.30	(4.85)	(2.02)
Value	1.15	1.05	0.97	1.29	1.30	0.16	0.92	0.91	0.89	1.02	0.97	0.05
	(4.68)	(4.44)	(4.16)	(5.20)	(5.05)	(0.67)	(4.28)	(4.17)	(4.41)	(5.15)	(3.76)	(0.23)
Profitability	1.00	1.11	1.17	1.01	1.63	0.62	0.87	0.94	0.93	0.88	1.03	0.16
	(4.22)	(4.48)	(4.68)	(4.23)	(6.31)	(2.89)	(4.34)	(4.42)	(3.95)	(3.82)	(4.97)	(0.95)
Investment	1.17	1.28	1.15	1.03	0.98	-0.19	1.19	1.01	0.95	0.94	0.90	-0.29
	(4.63)	(5.84)	(5.36)	(4.21)	(3.43)	(0.92)	(5.30)	(5.63)	(5.14)	(4.15)	(3.24)	(1.33)

Table 5. Stock Return Anomalies and Productive Efficiency (Equal-Weighted)

Low Efficiency					High Efficiency					
2	3	4	H	HML	L	2	3	4	H	HML
1.58	1.45	1.41	1.22	-0.77	1.50	1.36	1.26	1.18	1.06	-0.44
(4.77)	(4.64)	(4.91)	(5.17)	(3.29)	(5.09)	(4.54)	(4.40)	(4.36)	(4.82)	(2.26)
1.48	1.57	1.71	1.73	0.31	1.07	1.24	1.20	1.40	1.35	0.28
(4.63)	(5.23)	(5.82)	(6.07)	(1.71)	(3.86)	(4.56)	(4.71)	(5.53)	(4.99)	(1.60)
1.54	1.60	1.64	1.99	0.59	1.05	1.08	1.22	1.35	1.44	0.39
(5.27)	(5.34)	(5.40)	(6.34)	(3.96)	(4.05)	(4.19)	(4.53)	(5.13)	(5.39)	(3.10)
1.68	1.49	1.41	1.16	-0.77	1.57	1.34	1.33	1.23	1.01	-0.56
(6.26)	(5.52)	(4.76)	(3.50)	(5.58)	(5.97)	(5.74)	(5.85)	(4.79)	(3.21)	(3.58)

To show that our empirical results are not driven by the choice of weighting scheme, we report the results for the equal-weighted portfolios in Table 5. Our results not only remain robust but also they are statistically and economically stronger. In fact, now all the four anomalies are more significantly priced among low-efficiency firms. For example, the risk premia associated with the investment anomaly is -0.77% for low-efficiency firms, compared with -0.56% high-efficiency firms.

Overall, the effect of technical efficiency on the performance of the classical Fama-French four risk factors is pronounced and significant. This is consistent with our empirical evidence that low efficiency firms are more sensitive to economic shocks. Hence, investors do require higher compensation not only for lower efficiency itself (e.g., Nguyen and Swanson, 2009), but also for other risk factors.

5. Conclusion

This paper provides evidence about the importance of technical efficiency change, and thus its explanatory power for the TFP growth for a large sample of US firms over the period 1966-2015. For this purpose, we decompose TFP growth into three components: 1) returns to scale component; 2) technical progress; and 3) technical efficiency change. Although most of the TFP growth is due to technical progress, most of the variation in TFP growth is explained by technical efficiency change. Therefore, the portion of the TFP growth that is more sensitive to macro shocks turns out to be technical efficiency. Moreover, since time-varying technical efficiency reflects time-varying firm-level frictions, we study the effects of different efficiency levels on asset prices. Low efficiency firms are more sensitive to a variety of macroeconomic shocks, consistent with the theoretical role of frictions. Altogether, the classical stock return anomalies are more pronounced among low efficiency firms, in line with the conventional view that macroeconomic risks are amplified through firms with lower technical efficiency. A major policy implication of our results is that the information contained in the cross-section of technical efficiency could help policymakers to evaluate the sensitivity of different categories of firms to macroeconomic shocks.

Consequently, our evidence suggests that US economic policymakers should also consider measures of technical efficiency in the design and implementation of optimal allocation of resources to different classes of firms. Specifically, policy interventions should be directed to bridge the technology gap between low-efficiency and high-efficiency firms to smooth out the negative effects of macroeconomic shocks on the long-term potential growth of the US economy.

References

Aigner, D.J., Lovell, C.A.K., and Schmidt, P. (1977), Formulation and estimation of stochastic frontier production function models, *Journal of Econometrics*, 6, 21-37.

Avramov, D., Chordia, T., and Jostova, G. (2013), Anomalies and financial distress, *Journal of Financial Economics*, 108, 139-159.

Barro, R.J. and Lee, J.-W. (1993), International comparisons of educational attainment, *Journal of Monetary Economics*, 32, 363-394.

Barro, R.J. and Lee, J.-W. (1996), International measures of schooling years and schooling quality, *American Economic Review*, 32, 363-394.

Battese, G.E. and Coelli, T.J. (1992), Frontier production functions, technical efficiency and panel data: With application to paddy farmers in India, *Journal of Productivity Analysis* 3, 153-169.

Battese, G.E. and Coelli, T.J. (1995), A model for technical inefficiency effects in a stochastic frontier production function for panel data, *Empirical Economics* 20, 325-332.

Bernanke, B.S., Gertler, M., Gilchrist, S. (1999), The financial accelerator in a quantitative business cycle framework, *Handbook of macroeconomics*, 1, 1341-1393.

Brunnermeier, M.K. and Sannikov Y. (2014), A macroeconomic model with a financial sector, *American Economic Review*, 104, 379-421.

Caudill, S.B., Ford, J.M., and Gropper, D.M. (1995), Frontier estimation and firm-specific inefficiency measures in the presence of heteroskedasticity, *Journal of Business Economics and Statistics*, 13, 105-111.

Christiano, L.J., Eichenbaum, M., Evans, C.L. (2005), Nominal rigidities and the dynamic effects of a shock to monetary policy, *Journal of Political Economy*, 113, 1-45.

Demerjian, P., Lev, B., and McVay, S., (2012), Quantifying managerial ability: a new measure and validity tests, *Management Science*, 58, 1229-1248.

Espinoza, R.A., Prasad, A., Leon, M.H.L. (2010), Estimating the inflation-growth nexus: A smooth transition model, International Monetary Fund.

Fama, E.F. and French, K.R. (1993), Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics*, 33, 3-56.

Fama, E.F. and French, K.R. (1995), Size and book-to-market factors in earnings and returns, *Journal of Finance*, 50, 131-155.

Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. Journal of Financial Economics, 116(1), 1-22.

Fama, E.F. and French, K.R. (2016), Dissecting anomalies with a five-factor model, *Review of Financial Studie*s, 29, 69-103.

Fare, R., Grosskopf, S., Norris, M., and Zhang, Z. (1994), Productivity growth, yechnical progress, and efficiency change in industrialized countries, *American Economic Review*, 84, 66-83.

Gilchrist, S., Sim, J.W., and Zakrajšek, E. (2014), Uncertainty, financial frictions, and investment dynamics, *National Bureau of Economic Research*.

Gorodnichenko, Y. and Weber, M. (2016), Are sticky prices costly? Evidence from the stock market, *American Economic Review*, 106, 165-199.

Habib, M.A. and Ljungqvist, A. (2005), Firm value and managerial incentives: a stochastic frontier approach, *Journal of Business*, 78, 2053-2094.

Hadlock, C.J. and Pierce, J.R. (2010), New evidence on measuring financial constraints: moving beyond the kz index, *Review of Financial Studies*, 23, 1909-1940.

Hall, B.H. and Mairesse, J. (1995), Exploring the relationship between R&D and productivity in French manufacturing firms, *Journal of Econometrics*, 65, 263-293.

Hong, H., Sraer, D.A. (2016), Speculative betas, *Journal of Finance*, 71, 2095-2144.

Imrohoroglu, A. and Tuzel, S. (2014), Firm-level productivity, risk, and return, *Management Science*, 60, 2073-2090.

Kumbhakar, S.C. and Lovell, C.K. (2003), Stochastic frontier analysis. Cambridge University Press.

Kung, H., Schmid, L. (2015), Innovation, growth, and asset prices, *Journal of Finance*, 70, 1001-1037.

Lin, X. (2012), Endogenous technological progress and the cross-section of stock returns, *Journal of Financial Economics*, 103, 411-427.

Meeusen, W. and van den Broeck, J. (1977), Efficiency estimation from Cobb Douglas production functions with composed error, *International Economic Review*, 18, 435-444.

Nishimizu, M. and Page, J. (1982), Total factor productivity growth, technological progress, and technical efficiency change: Dimensions of productivity change in Yugoslavia, 1965-78, *Economic Journal*, 92, 920-936.

Nguyen, G.X. and Swanson, P.E. (2009), Firm characteristics, relative efficiency, and equity returns, *Journal of Financial and Quantitative Analysis*, 44, 213-236.

Olley, S. and Pakes, A. (1996), The dynamics of productivity in the telecommunications equipment industry, *Econometrica*, 64, 1263-1297.

Petkova, R. (2006), Do the Fama–French factors proxy for innovations in predictive variables? *Journal of Finance*, 61, 581-612.

Simon, H.A. (1955), A behavioral model of rational choice, *Quarterly Journal of Economics*, 69, 99-118.

Simon, H.A. (1957), Models of man, social and rational: Mathematical essays on rational human behavior in a social setting, New York: John Wiley and Sons.

Wang, H-J. (2002), Heteroskedasticity and non-monotonic efficiency effects of a stochastic drontier model, *Journal of Productivity Analysis*, 18, 241-253.