Understanding the Firm-Productivity Effect in Stock Returns

Tze Chuan 'Chewie' Ang[*]

F.Y. Eric C. Lam

K. C. John Wei

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ABSTRACT

We empirically evaluate mispricing- and risk-based explanations for the negative cross-sectional relation between firm-level productivity and stock returns (the 'firm-productivity effect') documented in previous studies. The evidence supports both explanations: investors over-extrapolate a firm's/stock's past performance, resulting in the mispricing of firm-productivity, and limits-to-arbitrage perpetuate the mispricing; (ii) the firm-productivity effect is related to distress risk, investment frictions, and exposure to macroeconomic shocks. Our decomposition tests show that variables related to past performance and limits-to-arbitrage explain most of the firm-productivity effect, followed by those related to distress risk, favoring mispricing-based explanations.

Keywords: Firm-level productivity; Extrapolation; Limits-to-arbitrage; Distress risk; Adjustment cost.

JEL classification: D23; D24; G12; G14

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[*] Ang, c.ang@deakin.edu.au, +61 3 924 46626, Department of Finance, Faculty of Business and Law, Deakin University. Lam, fyericcl@hkbu.edu.hk, +852 3411 5218, Department of Finance, Hong Kong Baptist University. Wei, johnwei@ust.hk, +852 2766 4953, Department of Finance, Hong Kong Polytechnic University and Hong Kong University of Science and Technology. This project was completed in part while Tze Chuan 'Chewie' Ang was completing his doctoral dissertation at the University of Melbourne. We are grateful to Andrew Ainsworth, Doug Foster, Roy Kouwenberg, Ben Marshall (discussant), Byoung-Kyu Min, Buhui Qiu, Takeshi Yamada, Qi Zeng, and the seminar participants at the SIRCA Young Researcher Workshop, Deakin University, Mahidol University, University of Adelaide, and University of Sydney for helpful comments and suggestions. All errors are our own. We thank Ken French, Selale Tuzel, and Jeffrey Wurgler for providing data.

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1. Introduction

A firm's productivity refers to its efficiency in converting inputs into output. Firm-level productivity shock plays a crucial role in neoclassical investment-based asset-pricing models in explaining the cross-sectional relation between stock returns and firm characteristics, such as the book-to-market ratio (Zhang, 2005), external financing (Li et al., 2009), financial constraints (Livdan et al., 2009), and labor hiring (Belo et al., 2014). The theoretical developments have motivated empirical studies that directly estimate firm-level productivity and examine its relation with returns (Nguyen and Swanson, 2009 and İmrohoroğlu and Tüzel, 2014). If firm productivity can explain the relation between many firm characteristics and stock returns, it should explain stock returns by itself. Indeed, empirical studies find a negative relation between firm productivity and future stock returns – the 'firm-productivity effect'.[1]

The prevailing explanations for the firm-productivity effect are risk-based. Building on neoclassical investment models, İmrohoroğlu and Tüzel (2014) show that unproductive firms face higher risk than their productive counterparts due to their steeper adjustment costs when they reduce their unproductive capital stock, especially during economic downturns. Hence, they attract a risk premium. On the other hand, Nguyen and Swanson (2009) argue that the high returns to unproductive firms may reflect the distress risk premium.

In this study, we propose mispricing-based explanations for the firm-productivity effect and provide further empirical evidence on risk-based explanations. We use the standard portfolio sorts and Fama-MacBeth regressions to analyze the role of risk- and mispricing-related variables in driving the firm-productivity effect. More importantly, we

[1] Although profitable firms are often more productive, the firm-productivity effect is different from the profitability puzzle documented by Novy-Marx (2013) – the positive cross-sectional relation between gross profit and stock returns. The firm-productivity effect is more closely related to the value/growth anomaly.

comprehensively test the fraction of the firm-productivity effect that is attributed to mispricing- or risk- related variables using the novel unified framework developed by Hou and Loh (2016). We also examine the connection between two seemingly unrelated measures of firm-productivity in explaining returns and address the robustness issues of the firm-productivity effect.

We use two measures for firm productivity: a firm's shortfall from its potential value frontier (Nguyen and Swanson, 2009) and its firm-level total factor productivity (İmrohoroğlu and Tüzel, 2014).[2] A long-short portfolio strategy based on firm-productivity earns a return of more than 1% per month, confirming the findings in previous studies. Our first extension to the literature is to show that the firm-productivity effect is robust even after controlling for Fama and French's (2015) new five factors and other common predictors of returns. Unproductive firms behave like small value firms that have suffered from bad past returns and operating performance, while productive firms are similar to large growth firms with good past returns and operating performance. Moreover, we show that the two measures of firm productivity are highly correlated. They produce an empirical distribution of firm characteristics that are similar despite their differences in inputs and modelling frameworks.

Our second contribution is to propose and test mispricing-related explanations for the firm-productivity effect in returns. The behavioral finance literature suggests that investors extrapolate past stock returns and firm performance too far into the future, resulting in the overreaction in stock returns when the realization of outcome is contrary to their expectation (e.g. De Bondt and Thaler, 1985, Lakonishok et al., 1994). Recently, Hirshleifer et al. (2015) show that perceived technological growth rate is negatively related to market returns because of extrapolative expectation and adjustment costs. Motivated by these findings, we hypothesize that investors with extrapolative bias form expectations of future firm

[2] We model the first measure using the parametric stochastic frontier approach (SFA) introduced by Aigner et al. (1977) and the second measure using the semi-parametric procedure suggested by Olley and Pakes (1996).

productivity growth based on past firm performance or productivity growth. They put greater weight on the recent realization of firm performance without considering its mean reversion to the base rate.

Our analysis shows that productive (unproductive) firms experience positive (negative) profit and productivity shocks prior to the portfolio formation year, but the trend reverses after the portfolio formation year. The reversal in firm performance and productivity coincides with the reversal in stock returns. Moreover, we find that investors correct most of their valuation errors about firm productivity around earnings announcements, when value-relevant information is released. Since risk-based explanations do not predict returns to be concentrated around information events (La Porta et al., 1997), our findings provide supporting evidence for the mispricing story.

We also use Baker and Wurgler's (2006) market-wide investor sentiment index to explore the role of investor sentiment. We find that the firm-productivity effect is stronger following months with high investor sentiment when speculative demand is high compared to months with low sentiment. The evidence suggests that investors appear to misprice firm-productivity in the cross-section of returns.

If the firm-productivity effect is driven by mispricing, why is the profit-making opportunity not exploited by arbitrageurs? The limits-to-arbitrage explanation (Shleifer and Vishny, 1997) suggests that anomalies persist because trading frictions hinder arbitrage trading. Specifically, (Pontiff, 1996, 2006) argue that arbitrageurs face a trade-off between arbitrage profits and the related costs. Arbitrageurs prefer to hold less stocks with high idiosyncratic volatility (for a given level of mispricing) because they are difficult to hedge. Transaction costs related to the initiation and termination of arbitrage positions would also reduce the incentive for arbitrageurs to eliminate mispricing. As a result, the mispricing takes longer to be corrected. Using a number of proxies for arbitrage and trading costs, we find that the firm-productivity effect is more pronounced in firms with high limits-to-arbitrage.

Our third contribution is to provide empirical evidence on the risk-related explanation of the firm-productivity effect based on existing theories. İmrohoroğlu and Tüzel (2014) suggest that unproductive firms are more exposed to aggregate productivity shocks than their productive counterparts because of their steeper adjustment costs, especially in recessions, when they reduce unproductive capital stock. Hence, they are more inflexible and this risk exposure is compensated by higher returns. We examine the role of adjustment costs in the firm-productivity effect from two angles: the financing and operating sides of a firm. We find that investment frictions accentuate the firm-productivity effect, but there is no empirical support for the role of operating costs. Furthermore, we show that unproductive firms are more sensitive to macroeconomic shocks than productive firms, using Chen et al.'s (1986) (CRR) macroeconomic factor model. Specifically, macroeconomic risk explains a large part of the return difference between firms with extreme levels of productivity, reducing the alpha to -0.56% per month. Nonetheless, we find that the firm productivity effect is persistent throughout our sample period, regardless of the macroeconomic conditions.

Another risk-based explanation for the firm-productivity effect is that unproductive firms face higher distress risk than productive firms (Nguyen and Swanson, 2009). Their high return compensates for distress risk. Using various proxies for distress risk, we find that unproductive firms are likely in financial distress. The return spread between high and low firm-productivity portfolios is the highest amongst distressed stocks.

Our fourth contribution is to measure the fraction of the negative relation between firm-productivity and stocks returns that is explained by risk- or mispricing-related variable under a unified framework, developed by Hou and Loh (2016). Our results show that past firm performance, past stock returns and limits-to-arbitrage (idiosyncratic volatility and bid-ask spread) account for the largest fraction of the firm-productivity effect, followed by distress risk. However, variables related to adjustment costs do not explain the firm-productivity effect. The best candidate variables that explain the firm-productivity effect appear to be related to mispricing, rather than risk.

Overall, the evidence suggests that investors' extrapolations of past performance drive them to overvalue (undervalue) firms with high (low) productivity and the mispricing adjusts when value-relevant information is released around earnings announcements. As such, our study adds to the growing literature on investors' overreaction to past information.[3] We also find that the high returns to unproductive firms are related to distress risk. Our finding is consistent with previous studies that highlight the role of financial distress in driving other asset-pricing anomalies (e.g. Avramov et al., 2013).[4]

Furthermore, we also show that limits-to-arbitrage impede the price adjustment towards fundamentals and allow the return-predictability based on firm productivity to persist. Our findings extend the literature that highlights the role of limits-to-arbitrage in driving the return predictability based on firm characteristics, such as Ali et al. (2003) (value effect), McLean (2010) (momentum and reversal), Lam and Wei (2011) (asset growth), and Li and Luo (2016) (cash holding). Moreover, we also find that investment frictions accentuate the firm-productivity effect, extending the literature on the role of frictions in asset-pricing (e.g. Li and Zhang, 2010).

The remainder of the paper proceeds as follows. Section 2 describes the data and measures of firm productivity. Section 3 presents the main empirical results. Sections 4 and 5 test the mispricing- and risk-based explanations of the firm-productivity effect, respectively. Section

[3] For example, previous studies show that investors' extrapolation of past stock and firm performance predict negative future abnormal returns (e.g. De Bondt and Thaler, 1985, Lakonishok et al., 1994, La Porta et al., 1997). Daniel and Titman (2006) find that investors overreact to hard-to-process intangible information.

[4] While our work focuses on firm's operating productivity, it is related to previous studies that examine the impact of others forms of firm-level efficiencies on stock returns. For example, Cohen et al. (2013) and Hirshleifer et al. (2013) show that investors are slow to incorporate information on innovative productivity in stock prices. Alan et al. (2014) find a positive relation between inventory productivity and stock returns.

6 performs the decomposition analysis of the fraction of the firm-productivity effect that is attributed to risk- or mispricing-related variables. Section 7 concludes.

2. Data and measures of firm productivity

2.1. Sample

The sample consists of all firms listed on the NYSE, AMEX, and Nasdaq from 1972 through 2015. Stock data are sourced from the Center for Research in Security Prices (CRSP).[5] Accounting data and earnings announcement dates are obtained from Compustat files. To mitigate backfilling biases, we exclude firms that are listed on Compustat for less than 2 years. We exclude financial (SIC codes 6000-6999) and regulated utility (SIC codes 4900-4999) firms. We also exclude stocks priced below $1 per share as at June every year. To avoid any look-ahead bias, all accounting variables are computed at the end of the fiscal year prior to the sorting year. A stock must have available data to compute the firm productivity measure to be included in the final sample.

2.2. Measuring firm productivity

We define firm productivity as a firm's ability to efficiently use its inputs to produce an optimal output. We measure firm productivity using two frameworks. In the first framework, we estimate firm productivity using the stochastic frontier analysis (SFA), pioneered by Aigner et al. (1977).[6] The intuition behind the SFA is as follows. Consider a set of firms with different characteristics facing the same opportunity set. Firms that can generate higher value per dollar of assets should fetch higher valuations. Once we have estimated the optimal value

[5] We use monthly delisting returns from the CRSP tapes if they are available. Following Shumway (1997) and Shumway and Warther (1999), we replace missing delisting returns with -0.30 for stocks delisted from NYSE or AMEX and -0.55 for stocks delisted from Nasdaq.
[6] This method is commonly used in the finance literature. For example, see Hunt-McCool, Koh, and Francis (1996), Habib and Ljungqvist (2005), and Nguyen and Swanson (2009).

frontier given various firm characteristics, a firm's shortfall from the frontier is the measure of investors' perception of firm inefficiency. Since the true optimal frontier is unobservable, a firm's shortfall from the frontier can be driven by its inefficiency or random noise. The SFA approach allows us to differentiate between random noise and firm-specific inefficiency, which is unidentifiable using the ordinary least squares (OLS) estimation method.

Following Nguyen and Swanson (2009), we choose the inputs according to underlying theory and previous empirical studies (e.g. Habib and Ljungqvist, 2005). We conduct Fama-MacBeth regressions of the following estimating model at the end of June every year to generate the measure of firm-level productivity:

$$\ln(ME_i) = \alpha + \gamma_j + \beta_1 \ln(BE_i) + \beta_2 D/A_i + \beta_3 CAPEX/SALES_i + \beta_4 RD/SALES_i + \beta_5 AD/SALES_i + \beta_6 PPE/A_i + \beta_7 EBITDA/A_i + \upsilon_i + \mu_i \quad (1)$$

where ME is market equity; BE is book equity; D/A is long-term debt over total assets; CAPEX/SALES, RD/SALES, and AD/SALES are capital expenditure, research and development expenses, and advertising expenses scaled by sales, respectively; PPE/A is property, plant and equipment scaled by total assets; EBITDA/A operating profits to total assets. The error term is decomposed into v_i, which is the random white noise that accounts for measurement errors and other random shocks beyond a firm's control (e.g. luck) and u_i captures a firm's inefficiency. We include Fama and French 49 industry dummies, γ to control for inter-industry differences in firm productivity. After estimating the parameters, we measure a firm's productivity score as follows:

$$Eff_i = \frac{E(V_i|u_i, X_i)}{E\left(V_i^*|u_i=0, X_i\right)} \quad (2)$$

where V^* is the frontier estimated firm value given no inefficiency.[7]

[7] The productivity score, *Eff$_i$*, is a normalized measure between 0 and 1. A score of 0.80 implies that a firm is valued at the 80% level compared to its best-performing peer in the sample. If all firms achieve optimal productivity (i.e. u_i = 0), then there is no gain in using the SFA. Following Habib and Ljungqvist (2005) and

To alleviate the concern that our measure of firm productivity is model-specific, we use an alternative measure: the total factor productivity (TFP) constructed by İmrohoroğlu and Tüzel (2014). Similar to the SFA measure, TFP measures a firm's efficiency in utilizing capital and labor units in generating output. They use the following production function:

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \omega_{it} + \eta_{it} \quad (3)$$

where y_{it} is the log of value added for firm i in period t, k_{it} and l_{it} are log values of the firm's capital and labor, ω_{it} is the TFP measure and η_{it} is the error term. The parameters are estimated using the semi-parametric procedure suggested by Olley and Pakes (1996).[8] The TFP is obtained after they estimate the production function parameters:

$$\omega_{it} = y_{it} - \widehat{\beta_0} - \widehat{\beta_k} k_{it} - \widehat{\beta_l} l_{it}. \quad (4)$$

This approach is better than the OLS approach as it controls for selection and simultaneity biases and within-firm serial correlation in productivity. With the use of industry-specific time dummies in the estimation, all TFP estimates are also free of industry or aggregate TFP effects in any year.

We perform every analysis and test in this study using both measures of firm-level productivity: the relative productivity measure implied by the SFA and TFP. The average yearly pair-wise correlation between both measures are around 0.40, which suggests that they contain much similar information about firm productivity/productivity. We interpret the differences between the firm-productivity measures as different aspects of firm productivity. In general, the results are qualitatively similar under both measures, so we only report those based on the SFA measure, unless a direct comparison is necessary.[9]

Nguyen and Swanson (2009), we test whether there is firm inefficiencies in our sample every year. Our test rejects the null hypothesis of $u_i = 0$ for all firm i, suggesting the need to use the SFA to model firm inefficiency.

[8] We source the TFP measure directly from Selale Tüzel. See İmrohoroğlu and Tüzel (2014) for details related to the estimation procedure.

[9] All the results under the TFP measure are available from the authors upon request.

3. Firm productivity, characteristics, and stock returns

3.1. Portfolio characteristics

We start by examining the firm characteristics of portfolios sorted by the firm productivity score (Eff). At the end of June each year, we estimate equation (1) and sort firms into 10 portfolios based on their productivity score as defined by equation (2). The portfolios are rebalanced annually. Table 1 reports the time-series mean of cross-sectional median firm characteristics. All variables are defined in Appendix A. Compared to their productive counterparts, unproductive firms are small value firms with lower asset growth. They also have low labor hiring and capital investment rates. Moreover, they have high leverage, but low market beta, profitability and past stock returns. Despite using completely different inputs and an alternative estimation method to generate firm-productivity, the portfolio characteristics sorted by firm-productivity (Eff) are similar to those reported by İmrohoroğlu and Tüzel (2014), who use the TFP measure. We extend their analysis by showing that unproductive firms face high distress risk as reflected by different measures of financial distress (i.e. Altman's (1968) Z-score, Ohlson's (1980) O-score and Merton's (1974) distance-to-default). Furthermore, unproductive firms are also illiquid and have high transaction costs, as implied by Amihud's (2002) price impact measure and other measures of trading costs. Most of the variables exhibit an almost monotonic relation in the firm-productivity spectrum. However, there is a 'U-shaped' pattern in the average portfolio idiosyncratic volatility (IVOL) as we move from the portfolio with the lowest productivity to that with the highest productivity. The extreme portfolios (those with the lowest and highest firm efficiencies, respectively) have the highest IVOL. The high IVOL may deter arbitrageurs from trading these portfolios.

3.2. Portfolio returns and factor loadings

We examine the portfolio returns from July of the sorting year to June of the following year. Panel A of Table 2 presents the mean monthly equally-weighted average portfolio returns sorted using both the Eff and TFP measures. They are the time-series mean of monthly cross-sectional average excess returns and the alphas with respect to the Capital Asset Pricing Model (CAPM), as well as Fama and French’s (1993), Carhart’s (1997), and Fama and French’s (2015) factor models. Consistent with Nguyen and Swanson (2009), who use the Eff measure, productive firms have significantly lower returns than unproductive firms and the spread range from -0.96% to -1.33% per month (t-stats from -6.90 to -9.64). Using İmrohoroğlu and Tüzel's (2014) TFP measure, the corresponding spreads are around -0.50% (t-stats of around 3.00). Moreover, the average portfolio returns decrease monotonically as firm productivity increases. Controlling for the market, size, value, momentum, profitability, and investment factors generally reduces the magnitude of the alpha, but do not change the tenor of the results.

Panel B of Table 2 shows the factor loadings with regards to the factor models. Productive firms are more sensitive to the stock market performance (market factor), as well as the profitability and momentum factors, than unproductive firms. However, they are less sensitive to both the size and value factors compared to their unproductive counterparts. The spread portfolio has significant positive loadings on the market and momentum factors, weakly positive loadings on the profitability factor, but significantly negative loadings on the size and value factors. It does not co-vary significantly with the investment factor. Overall, the returns on productive firms are similar to large growth stocks with high past returns and accounting profits. The returns on unproductive firms behave like small value stocks with low past returns and accounting profits.

3.3. Fama-MacBeth regressions

We run Fama-MacBeth regressions to control for other predictors of future stock returns documented in the previous studies. Panel C of Table 2 presents the results. Using different proxies for firm-productivity, we confirm the negative relation between firm-productivity and future returns in the univariate tests in Models 1 and 2. However, when we include both measures of firm-productivity in Model 3, only the coefficient on the Eff measure remains significant. In Model 4, we add the control variables: size, book-to-market ratio, past six-month returns (momentum), and previous-month return (reversal). Consistent with the literature, size and previous month return negatively predict return, while book-to-market ratio and momentum positively predict return. When we include the Eff measure in Model 5, it absorbs the explanatory power of both size and book-to-market ratio, but slightly improves that of momentum. However, when we include the TFP measure in Model 6, its explanatory power is subsumed by the control variables. Furthermore, in Models 7 to 9, we show that asset growth and leverage negatively predict returns and profitability is positively related to returns, but they do not subsume the predictive power of firm-productivity.[10]

So far, we have established the negative relation between firm productivity and stock returns as documented in the literature (see Nguyen and Swanson, 2009 and İmrohoroğlu and Tüzel (2014). In addition, we find that the firm-productivity measure generated using the SFA is a strong predicator of returns, even after controlling for other predictors of returns. In contrast, the TFP measure is subsumed by both the SFA measure and other control variables. For the remainder of the paper, we test whether risk- or mispricing-based stories better explain the negative relation using mainly portfolio sorts and Fama-MacBeth regressions.

[10] Unreported results also show that the input variables in the SFA model do not explain returns. We also tried various proxies for growth, such as inventory growth, sales growth, and investment growth, and different measures of profitability, such as net income over assets. Firm-productivity (Eff) still retains its significance in explaining the cross-sectional variations in stock returns even with the presence of these variables in the regressions. We do not tabulate the results to conserve space.

4. Testing the mispricing-based hypotheses

The behavioral finance literature (e.g. Barberis and Thaler, 2003) suggests that certain stocks are prone to mispricing due to their characteristics and limits-to-arbitrage perpetuate the mispricing. In this section, we explore the roles of investors' overextrapolation of past performance, limits-to-arbitrage, and investor sentiment in driving the firm-productivity effect.

4.1. Extrapolation of past performance and expectation errors

Previous studies find that some investors are subject to extrapolative biases (e.g. Hirshleifer, 2001). Empirical evidence shows that investors may extrapolate stock returns (De Bondt and Thaler, 1985) and firms' past performance (Lakonishok et al., 1994) too far into the future and overreact when the realized outcome is contrary to their naïve expectation. Survey evidence also shows that investors form expectation based on past stock returns (Greenwood and Shleifer, 2014).[11]

Recently, Hirshleifer et al. (2015) show that perceived technological growth rate negatively predicts aggregate stock returns in the presence of extrapolative bias and adjustment costs within a production-based asset-pricing framework with recursive preference. We extend their idea of extrapolative bias in productivity growth from the aggregate market-level to the firm-level. We hypothesize that investors with extrapolative bias may form expectations of future firm productivity by extrapolating past firm productivity (or earnings) of productive (unproductive) firms too far into the future, but are unpleasantly

[11] Both surveys and experimental studies show that investors' forecasts reflect trend-following mechanism (De Bondt, 1993). Barberis et al. (2015) find that a model with extrapolative investors is consistent with empirical patterns in returns and investors' expectations in surveys.

(pleasantly) surprised by the unexpected outcome.[12] They may put greater weight on the recent realization of productivity growth without adequate consideration of the mean reversion in operating performance or productivity growth (see Kahneman et al., 1982).

Following Lakonishok et al. (1994), we test the extrapolation hypothesis by observing the past and future firm performance, given the valuation ratios as proxy of investors' expectation. We start testing this hypothesis by examining the valuations ratios during portfolio formation. The high valuation ratio (i.e. low book-to-market ratio) for productive firms and low valuation ratio for unproductive firms (in Table 1) imply that investors are optimistic about productive firms' future growth, but pessimistic about unproductive firms' future growth. Next, we examine whether there is a reversal between pre- and post-formation firm productivity and operating performance with a similar pattern in stock returns. This pattern is consistent with investors' correction in valuation error. We plot the trend in firm productivity scores and operating performance (both level and change) over the period before and after the portfolio formation year in Figures 1 and 2. The averages and test statistics are reported in Panels A and B of Table 3.

We see a general trend of mean reversion in firm productivity. Productivity in productive firms increases in the years prior to the portfolio formation year, but decreases thereafter. In contrast, unproductive firms' productivity deteriorates before portfolio formation, but improves thereafter. The average changes in productivity pre- and post-portfolio formation are significant for both groups of firms. Furthermore, we find that unproductive (productive) firms consistently experience negative (positive) profit shocks until the portfolio-formation year (Year -1), after which they face a reversal in operating performance. The reversal in performance is particularly acute in the extreme portfolios: the most productive and

[12] Given the close correlation between a firm's productivity and its operating performance, such as sales and earnings growths, investors can infer past firm productivity from past firm performance even if investors cannot compute firm productivity easily.

unproductive firms. Again, the average changes in operating performance over the period are significant for both groups of firms.

Next, we examine whether investors are surprised by the reversal in firm performance post-portfolio formation by relating it with their stock return reactions. Figure 3 and Panel C of Table 3 show that the annual buy-and-hold returns sorted by firm productivity follow the pattern in the firms' operating performance. Productive (unproductive) firms experience years of high (low) returns when they have continuous positive (negative) earnings and productivity shocks, but the returns reverse following the sorting year when the positive (negative) operating performance and productivity growth reverse. The return patterns suggest that investors are surprised by the reversals in firm productivity and operating performance, especially in firms at the extreme ends of productivity.

La Porta et al. (1997) suggest that any risk-based explanation of a return pattern would not predict a significant difference in returns between information events (e.g. earnings announcements) and non-information events. In contrast, any mispricing is expected to be corrected disproportionately around future earnings announcements when value-relevant information is released. To differentiate between risk- and mispricing-based explanations, we examine whether investors are surprised by the unanticipated good (bad) news in unproductive (productive) firms around earnings announcements in the year following portfolio formation.[13] Following La Porta et al. (1997), we measure earnings announcement returns (EARs) as equally-weighted daily returns within the 3-day window around earnings announcements. All EARs are in the period from July of the sorting year through June of the following year. The average EARs are the time-series average of quarterly cross-sectional mean EARs. Average non-EARs are the average daily returns of all other trading days.[14]

[13] The earnings announcements are contemporaneous with the period when the most acute reversals in operating performance, productivity, and stock returns occur.
[14] In unreported tests, we also compute abnormal returns that account for market returns. The results are similar.

In Panel A of Table 4, we report the average EARs and non-EARs sorted by firms' productivity score. First, low productivity firms experience positive earnings surprise (average EAR = 0.341%), but high productivity firms suffer from negative earnings surprise (average EAR = -0.009%) and the difference is -0.350% per day (t-stats = -6.91). Second, the return spread between productive and unproductive firms during earnings announcements (-0.350%) is three times the spread on non-announcement days (-0.096%) and the difference is -0.254% per day (t-stats = -5.56). Furthermore, the average return difference between EARs and non-EARs for unproductive firms is 0.178% and -0.076% for productive firms. For comparison, we show the average annual buy-and-hold returns in Panel B. The difference in average annual returns between productive and unproductive firms is around -15%. The magnitude of price adjustments around earnings announcements (4 quarters x 3 days per quarter x -0.35% = 4.2%) is large in relation to the annual buy-and-hold returns. The evidence suggests that most of the correction of errors in valuation, occur around earnings announcements.

Overall, our findings support the extrapolation hypothesis. Investors appear to extrapolate firms' past productivity, operating performance, and returns too far into the future. Investors are surprised by the unexpectedly good (bad) news in unproductive (productive) firms and stock prices adjust around earnings announcements to reflect the correction of expectation errors.

4.2. Limits-to-arbitrage

Trading strategies based on firm-productivity generate high returns. Even if certain investors suffer from psychological biases (e.g. extrapolative of past performance), such a large profit opportunity will attract arbitrage-trading by sophisticated investors. In a frictionless word, arbitrageurs can costlessly buy undervalued securities and sell overvalued securities until security prices revert back to their fundamental values. However, mispricing may persist with the existence of limits-to-arbitrage, such as initiation, holding, and transaction costs, which outweighs the benefits of arbitrage-trading (see Pontiff, 2006).[15] Moreover, noise traders' unpredictable actions may delay price correction by making arbitrage risky De Long et al., 1990, Shleifer and Vishny,1997).

We hypothesize that the persistence in return predictability based on firm productivity is driven by arbitrage costs that slow the adjustment of prices to their fundamental values. We test this hypothesis by examining whether the firm productivity effect is stronger in firms with high limits-to-arbitrage. First, we follow the literature (e.g. Ali et al., 2003, Lipson et al., 2011) and use idiosyncratic volatility (*IVOL*) as a measure of arbitrage risk. Specifically, we compute IVOL as the standard deviation of the residuals from a regression of daily stock returns in month t-1 on the Fama and French (1993) three factors, following Ang et al. (2006). Pontiff (1996, 2006) suggest that arbitrageurs consider the trade-off between the profits from predictable patterns in returns and their exposure to *IVOL*. They prefer to hold lower proportions of stocks with high *IVOL* (for a given level of mispricing) due to hedging difficulties, resulting in a slower correction of stock prices back to their fundamental values. *IVOL* is particularly crucial in arbitrage-trading based on firm-productivity because the returns effect persists for an extended period of time after portfolio formation, which increases arbitrageurs' holding costs and arbitrage risk.

Second, we examine different measures of transaction costs as limits-to-arbitrage. Our tests are motivated by Shleifer and Vishny (1997), who argue that capital constrained arbitrageurs may have to terminate their trades prematurely to prevent further losses. First, we use Amihud (2002) price impact measure (*AMI*), which is computed as the ratio of the absolute value of daily stock returns to the daily dollar trading volume. AMI measures the

[15] Many studies explore the role of limits-to-arbitrage in driving the return-predictability using firm characteristics, such as the book-to-market ratio and asset growth. See Lipson et al. (2011) for a comprehensive list.

impact of order flow on stock prices. Our next measure is the effective bid-ask spread (BASK), defined as two times the difference between the transaction price and the mid-quote scaled by the transaction price. BASK proxies for the trading expenses that arbitrageurs compensate dealers for providing liquidity. We also examine the dollar trading volume (*DVOL*), defined as the number of shares traded multiplied by the stock price. DVOL inversely reflects the price pressure and time required to fill an order or to trade a large block of stocks.[16]

We independently sort firms into quintiles based on their productivity score and a proxy for limits-to-arbitrage, in turn. Panels A to D of Table 5 report the portfolio returns. We observe two general patterns. First, the firm productivity effect strengthens as we move from portfolios with low to high limits-to-arbitrage. For example, the return difference between portfolios with extreme firm efficiencies monotonically increases from -0.30% in the portfolio with low IVOL to -1.75% in the portfolio with high IVOL. A similar trend exists in the portfolio returns sorted by other proxies for limits-to-arbitrage (BASK, AMI, and DVOL). Second, the firm productive effect is strong in portfolios with high limits-to-arbitrage (high IVOL, BASK, and AMI; low DVOL), but is weak or non-existent in portfolios with low limits-to-arbitrage (low IVOL, BASK, and AMI; high DVOL).

Furthermore, we use the Fama-MacBeth framework to control for other characteristics that explain stock returns. We include a proxy for arbitrage cost and an interactive variable with the firm productivity measure, in turn. If arbitrage costs is a necessary condition for the firm-productivity effect, we expect the cross-sectional relation between firm productivity and returns exists only when arbitrage costs are high (i.e. the coefficient on the interaction variable is significantly negative, but not the coefficient on firm productivity).

[16] We also carried out a series of robustness checks using other proxies for illiquidity, information uncertainty, and/or transaction costs, such as stock price, analyst coverage, and dispersion in analysts' earnings forecasts. The results are qualitatively similar and available upon request.

Panel E of Table 5 presents the results. In all models (except Models 2 and 4), firm productivity still shows a significantly negative relation with stock returns after controlling for different types of arbitrage costs. Most proxies for limits-to-arbitrage are also significant in explaining future stock returns in the presence of other variables. For example, high IVOL predicts negative returns and high AMI predicts positive returns. Model 2 shows that the interaction coefficient with IVOL is a significant -1.25 (t-stats = -6.02), but the coefficient on firm productivity is insignificant. We see a similar pattern in Model 4 with BASK. The results suggest that firm productivity only negatively predicts returns when IVOL or BASK is high.[17]

In sum, the results show that binding limits-to-arbitrage, especially high holding cost (IVOL) and bid-ask spread (BASK), allow for the firm-productivity effect in returns to persist.

4.3. Investor sentiment and the firm-productivity effect

Previous studies show that investor sentiment can result in the mispricing of stocks and affect returns to stocks with subjective valuation and high sensitivity to speculative demand (Baker and Wurgler, 2006). Unproductive firms tend to be small unprofitable firms with high growth potential, idiosyncratic volatility, and distress risk (see Table 1). These characteristics make them difficult to value, but they are potentially attractive to speculators and optimists. We hypothesize that the propensity to speculate on their future potential is high when investor sentiment is high. Following Stambaugh et al. (2012), we test whether the firm-productivity effect in returns is stronger when investor sentiment is high. We measure investors' sentiment using the market-based sentiment index constructed by Baker and

[17] This finding is analogous to Lipson et al.'s (2011) finding that idiosyncratic risk is an important impediment of arbitrage that perpetuate the asset-growth effect in returns.

Wurgler (2006).[18] We classify a month as a high- (low-) sentiment month if the value of Baker and Wurgler's sentiment index in the previous month is above (below) the median value of our sample period. In Table 6, we show that the return spread between the high and low firm-productivity portfolio is -0.92% following low investor-sentiment, but it is -1.47% (or 50% more) following high sentiment and the difference is a significant -0.56% (t-stats = -2.04). The stronger firm-productivity effect when investor sentiment is high is consistent with investors mispricing firm-productivity in the cross-section of returns.

5. Testing the risk-based hypotheses

A risk-based hypothesis for the firm-productivity effect suggests that returns are higher for unproductive firms because they are fundamentally risker than productive firms. In this section, we investigate the roles of three risk-based explanations: adjustment costs, distress risk, and macroeconomic risk.

5.1. Adjustment costs

Adjustment costs are pivotal in neoclassical investment-based asset-pricing models in generating the cross-sectional relation between several firm characteristics and stock returns. For example, Zhang (2005) find that value firms are more risky (and hence they earn a premium) because of their higher adjustment costs in reducing unproductive assets, particularly during economic downturns compared to growth stocks. Other studies adopt the role of adjustment costs and/or productivity shock in explaining the relation between stock returns and a particular firm characteristic, such as financial constraint (Livdan et al., 2009), inventory growth (Jones and Tüzel, 2013), and labor hiring (Belo et al., 2014). In particular,

[18] The sentiment index is based on six sentiment proxies: the close-end fund discount, NYSE share turnover, the number of initial public offerings, the average first day's returns of initial public offerings, the equity share in new issue, and the dividend premium.

İmrohoroğlu and Tüzel (2014) suggest that unproductive firms incur a higher adjustment cost while disinvesting their capital stock in periods with negative aggregate productivity shocks compared to their productive counterparts. Through a parameterized model, they show that the adjustment costs, coupled with the countercyclical Sharpe ratios translate to an equity risk premium for unproductive firms (those with low Eff). They also argue that operating leverage disproportionally affects unproductive firms and amplifies the firm-productivity effect in stock returns.

In this section, we provide direct empirical tests on the role of adjustment costs in driving the firm-productivity effect. We use two proxies for adjustment costs: a composite score for investment frictions, which is closely related to the financing side of a firm, and firm-level operating cost, which is important for the operational side of a firm. The input variables for our composite score for investment frictions follow Li and Zhang (2010) and Lam and Wei (2011). The composite score (FRISC) is the average percentile rank of a firm's age, total assets, and payout ratio. A high score corresponds to high investment frictions. Following Novy-Marx (2011), we measure operating cost as the sum of cost of goods sold (COGS) and selling, general, and administrative expenses (SGA), scaled total assets. If adjustment costs play a role in the firm productivity effect, we expect the effect to be more pronounced amongst stocks with high operating costs.

In Panel A of Table 7, we report the returns on portfolios independently sorted by FRISC and firm-productivity. The return spread on the portfolios with extreme levels of firm-productivity increases from -0.22% to -1.56% as we move from the portfolios with low investment frictions to those with high investment frictions. Moreover, the return spread is the highest in the portfolio with the largest investment frictions. However, when we examine the results sorted by operating cost (OC) and firm-productivity in Panel B, we do not find supporting evidence for the adjustment cost hypothesis. The negative return spread between portfolios with extreme levels of firm-productivity is the highest in firms with medium level of OC, but is the lowest in firms with low or high OC. Nonetheless, there is some evidence that the spread between unproductive firms with high OC and productive firms with low OC is high (-1.31%), whereas the spread between unproductive firms with low OC and productive firms with high OC is low (-0.31%), suggesting that the high OC in unproductive firms corresponds to high returns.

Panel C of Table 7 shows the results from Fama-MacBeth regressions, in which we include a proxy for adjustment costs and an interaction term with the firm-productivity measure (Eff), along with other control variables. Model 1 shows that investment frictions do not predict returns once control variables are included. However, in Model 2, we see that the interaction term is significantly negative, suggesting that firm productivity only predicts negative return when investment frictions are large. Model 3 shows that firm productivity still predicts negative returns (-3.977) and OC predicts positive returns (0.105), in the presence of each other. Nonetheless, the power of OC in explaining returns disappears with the inclusion of the interaction term.

Overall, the empirical evidence supports the prediction from İmrohoroğlu and Tüzel's (2014) theoretical model with regards to adjustment costs, but not operating leverage. Our findings suggest that adjustment costs from the financing side of a firm (investment frictions), but not the operating side (operating costs) contribute to a more pronounced firm-productivity effect in stock returns.

5.2. Distress risk

Distress risk is related to many asset-pricing anomalies, such as the momentum, asset growth, dispersion of opinion effects in stock returns (Avramov et al., 2013). Nguyen and Swanson (2009) note the possible role of distress risk in driving the negative relation between firm productivity and stock returns. The characteristics of unproductive firms in Table 1 suggest that they are in financial distress. Their high abnormal returns may compensate for their high distress risk (see Vassalou and Xing, 2004). If distress risk drives the firm-productivity effect in the cross-section of returns, we would expect the effect to exist only in firms with high distress risk or in financial distress, but not in healthy firms.

To test the distress risk hypothesis, we examine the returns on stocks independently sorted by distress risk and firm productivity. We use three proxies for distress risk: Merton's (1974) distance-to-default, Ohlson's (1980) O-score, and Altman's (1968) Z-score.[19] A high distress score indicates a high likelihood of financial distress. Panels A through C of Table 8 present the results. Two trends emerge throughout the panels. First, the negative relation between firm-productivity and returns is the strongest in the portfolios with the highest distress risk. The return spreads in the portfolios with the highest distress risk range from -1.1% to -1.3% compared to around -0.6% to -0.8% in the portfolios with the lowest distress risk. Second, Panels A and C show that the firm-productivity effect becomes monotonically stronger as we move from portfolios with low to high distress risk.

In Panel D of Table 8, we include distress risk and an interaction term of firm productivity and distress risk in Fama-MacBeth regressions with other control variables. If the firm-productivity effect is driven by financial distress, the interaction term should be significantly negative and the coefficient on firm productivity should be insignificant. The results in Models 1, 3, and 5 show that distress risk negatively predicts future returns, confirming the distress risk puzzle in previous studies (see Campbell et al., 2008). However, firm productivity remains a significant negative predictor of future returns even after controlling for distress risk in all models. The interaction term with distress risk is mostly insignificant, apart from that in Model 4.

[19] See Appendix A for the detailed definitions.

In sum, distress risk exacerbates the negative relation between firm-productivity and returns. Nonetheless, the firm-productivity effect still exists in firms with low distress risk, suggesting that distress risk alone is not the complete explanation.[20]

5.3. Macroeconomic risk

İmrohoroğlu and Tüzel (2014) suggest that unproductive firms earn higher stock returns than their productive counterparts because investment frictions make them are more exposed to economic downturns. To test this hypothesis, we track the performance of a trading strategy that goes long on stocks in unproductive firms and short on stocks in productive firms across our sample period. If risk is the explanation, we would expect stocks in unproductive firms to attract a high risk premium compared to their productive counterparts in bad states of the economy when the marginal utility of consumption is high, especially to risk-averse investors (see Lakonishok et al., 1994, İmrohoroğlu and Tüzel, 2014). We proxy for bad states of the economy using economic contractions (recessions) as defined by the National Bureau of Economic Research (NBER).

Figure 4 shows that the long-short trading strategy based on extreme firm-efficiencies is persistently profitable throughout our sample period. It generates an average return of 1.2% per month, regardless of the state of the economy. Stocks in unproductive firms outperform their productive counterparts in 34 out of 42 years without showing any extreme outperformance in recessions. This pattern contrasts with İmrohoroğlu and Tüzel's (2014)

[20] Avramov et al. (2013) show that the profitability of many trading strategies based on asset-pricing anomalies relies on the short position in firms under financial distress. In contrast, the firm-productivity effect still exists even after we remove distressed firms (i.e. those with junk bond rating) from our sample in unreported tests. Unlike many other anomalies, a trading strategy based on differences in firm productivity requires arbitrageurs to long firms with low firm productivity (which also have high distress risk) and short firms with high productivity (which have low distress risk). The trading strategy is more closely related to value-investing, in which investors long value stocks (which have low firm productivity) and short growth stocks (which have high firm productivity).

finding that unproductive firms offers high risk premium in economic recessions (periods with low aggregate productivity) compared to productive firms.

We formally test whether the negative firm-productivity stock-returns relation is associated with macroeconomic risk using Chen et al.'s (1986) (CRR) macroeconomic-based factor model. We create CRR's macroeconomic risk mimicking portfolios based on 40 test portfolios: 4 x 10 equally-weighted portfolios sorted on size, book-to-market, momentum, and firm-productivity, respectively. If exposure to macroeconomic risk drives the firm-productivity effect, we expect the CRR factors to explain most of the abnormal returns.

Table 9 presents the alphas and betas with respect to CRR's model. Unproductive (Productive) firms still generate significantly positive (negative) abnormal returns (alphas). However, the return spread drops drastically to -0.56% (from around -1.00% in Panel A of Table 2) and the alphas in many non-extreme portfolios become insignificant. The reduced magnitude of alphas suggests a significant improvement of the CRR model in explaining the cross-section of returns sorted on firm productivity as compared to Fama and French's factor models (see Panel A of Table 2). Moreover, we observe that unproductive firms are more sensitive to macroeconomic risk factors, such as the growth rate in industrial production (MP) and unanticipated changes in inflation (UI), risk premium (URP), and the term structure (UTS), than their productive counterparts. This finding provides some empirical support to İmrohoroğlu and Tüzel's (2014) model that links together firms' characteristics, their exposure to productivity shocks, and stock returns.

In short, CRR's macroeconomic factor-model better explains the cross-sectional variation in returns across the firm-productivity spectrum. Nonetheless, macroeconomic risk still does not fully explain the firm-productivity effect in returns.

6. Decomposing the firm-productivity effect

So far, we have examined the role of a particular risk- or mispricing-related variable in driving the firm-productivity effect in isolation. We have shown that investors' extrapolation of past performance appears to be related to the firm-productivity effect and the effect is stronger in stocks with binding limits-to-arbitrage, high investment frictions, and high distress risk. Nonetheless, a direct comparison of the strength of different variables in driving the firm-productivity effect is difficult in the commonly used portfolio-sort and Fama-MacBeth regression frameworks reported in previous sections. Moreover, it is impossible to disentangle the effect of a potential variable in explaining the firm-productivity effect if it is closely related to firm-productivity, but is subsumed by firm-productivity in multivariate regressions.

In this section, we evaluate the fraction of the firm-productivity effect that is explained by a candidate variable by itself and after controlling for other competing variables within a unified framework that allows for direct comparison across different variables. Our decomposition analysis follows the framework developed by Hou and Loh (2016). In Stage 1, we perform monthly Fama-MacBeth cross-sectional regressions of individual characteristic-adjusted stock returns on the firm-productivity score (Eff):

$$R_{it} = \alpha_t + \beta_t Eff_{it-1} + \varepsilon_{it} , \quad (5)$$

where R_{it} is the stock return after adjusting for market capitalization, book-to-market ratio, previous-month return, and past six-month returns.[21] In Stage 2, we add a candidate variable (X_{it-1}) to the cross-sectional regression, in turn:

$$R_{it} = \tilde{\alpha}_t + \tilde{\beta}_t^R Eff_{it-1} + \tilde{\beta}_t^C X_{it-1} + \tilde{\varepsilon}_{it}, \quad (6)$$

where X_{it-1} is a candidate variable (e.g. distress risk or idiosyncratic volatility) that may explain the firm-productivity effect. This stage allows us to assess the power and robustness

[21] R_{it} is the residual from the monthly regression of raw stock returns on size, BM, PRET, and MOM.

of firm-productivity (Eff) in explaining future returns in the presence of the candidate variable. In Stage 3, we regress Eff on a candidate explanatory variable (X_{it-1}), in turn:

$$Eff_{it-1} = a_{t-1} + \delta_{t-1}X_{it-1} + \omega_{it-1}. \quad (7)$$

This stage allows us to examine the relation between Eff and the candidate variable. A candidate variable that has the potential to explain the firm-productivity effect should be correlated with Eff. However, having a high correlation with Eff does not guarantee that the candidate variable will explain a large portion of the firm-productivity effect because the candidate must also be able to explain stock returns, by itself. In Stage 4, we use the linearity of covariances to decompose the estimated coefficient (β_t) in Equation (5), into two portions:

$$\begin{aligned}
\beta_t &= \frac{Cov[R_{it}, Eff_{it-1}]}{Var[Eff_{it-1}]} \\
&= \frac{Cov\left[R_{it}, (\delta_{t-1}X_{it-1} + a_{t-1} + \omega_{it-1})\right]}{Var[Eff_{it-1}]} \\
&= \frac{Cov\left[R_{it}, (\delta_{t-1}X_{it-1})\right]}{Var[Eff_{it-1}]} + \frac{Cov\left[R_{it}, (a_{t-1} + \omega_{it-1})\right]}{Var[Eff_{it-1}]} \\
&= \beta_t^C + \beta_t^{\varepsilon}. \quad (8)
\end{aligned}$$

β_t^C/β_t measures the fraction of the firm-productivity effect explained by the candidate explanatory variable and $\beta_t^{\varepsilon}/\beta_t$ measures the fraction left unexplained.[22] We group our candidate variables into those related to past performance, limits-to-arbitrage, and risk in our analysis.

We start by focusing on the univariate analysis in Panels A through C of Table 10. All of the coefficients on firm-productivity in Stage 1 are significant and they range from a -1.1 to -2.5, confirming the negative relation between firm-productivity and returns. When we add the candidate variable in Stage 2, the magnitude of the coefficients on firm-productivity barely changes. Most of the coefficient on the candidate variables are significantly negative

[22] See Hou and Loh (2016) for details on the derivations and test statistics.

(except for PΔROA, AMI, OC, and Z with positive coefficients), which suggest that they predict negative returns, even after controlling for firm productivity.

In Stage 3 (Panel A of Table 10), we see that the variables related to past performance are significantly positively related to firm productivity (Eff). The adjusted R^2s suggest that both past three-year mean annual return (PYRET) and changes in productivity (PΔEFF) explain around 15% of the variations in Eff, each. In contrast, Panels B and C show that the variables related to limits-to-arbitrage and risk are negatively related to firm productivity (apart from OC and Z). This result corroborates our finding that the firm-productivity effect is stronger in stocks with high distress risk and only exists in stocks with high limits-to-arbitrage and investment frictions. However, the adjusted R^2s are mostly below 6% (except for O), indicating a lack of relation between Eff and those variables.

When we decompose the coefficient of Eff in Stage 4, we find that, the variables related to past performance explain around 25-30% of the firm-productivity effect in the best cases. Specifically, PYRET and PΔEFF are the most successful variables, followed by PΔROA. Furthermore, the insignificant coefficients on the candidate variables ($\tilde{\beta}_t^C$) in Stage 2 regressions and the positive correlation between Eff and past performance in Stage 3 regressions imply that the part of past performance (PYRET and PΔEFF) that is related to Eff predicts future returns. Together, these findings provide further support to the extrapolation of past-performance hypothesis in explaining the firm-productivity effect. In addition, consistent with the results in Section 4, candidate variables related to limits-to-arbitrage (IVOL and BASK) play a significant role (15%) in explaining the firm-productivity effect. However, the negative correlation between Eff and limits-to-arbitrage and the results in Section 4 suggest that the sub-group of firms with high limits-to-arbitrage predicts future returns. This result in consistent with the interpretation that limits-to-arbitrage perpetuate the firm-productivity effect. On the other hand, variables related to distress risk explain only 5-

10% of the firm-productivity effect, while adjustment costs score between -1 to 3%.[23] This finding suggests that distress risk and operating cost, by themselves, explain the cross-section of returns well, but they are less successful in explaining the firm-productivity effect.

So far, we have examined the fraction of the firm-productivity effect explained by a candidate variable in isolation. Now, we perform a multivariate analysis of the marginal contribution of each variable after controlling for competing variables. Our analysis will also show the total fraction explained by all the candidate variables and the fraction unexplained. Panel D of Table 10 reports the results. The adjusted R^2 in Stage 3 regression indicates that 40% of the variations in Eff is explained by the 12 candidate variables. In Stage 4 regression, we see that around 50% of the firm-productivity effect is explained by the 12 candidate variables, leaving the other 50% (t-stats = 5.88) unexplained. The variable that explains the most of the effect is idiosyncratic volatility, IVOL (19%), followed by past three-year returns, PYRET (17%). The next largest contributors are distress risk, Z (15%) and bid-ask spread, BASK (14%). The rest of the variables have marginal contribution to the firm-productivity effect. Together as a group, variables related to limits-to-arbitrage contributes to 26% of the firm-productivity effect, followed by those related to past performance (20%), and distress risk (6%). Variables related to adjustment costs do not have significant explanatory power.

Overall, our results suggest that variables related to the mispricing of past performance and limits-to-arbitrage show considerable success in explaining the firm-productivity effect compared to those related to risk. Nonetheless, a large fraction (50%) of the returns pattern remains unexplained.

[23] The fraction explained by operating cost (OC) is significantly negative because the adding-up constraint in Stage 4 requires the OC and the residual component to add up to the Stage 1 coefficient on Eff (see Hou and Loh, 2016). OC predicts positive returns and is also positively related to Eff, so it does not explain the negative relation between firm-productivity and returns. Hence, its contribution is negative.

7. Conclusion

In this study, we propose mispricing-based explanations for the negative cross-section relation between firm productivity and stock returns (the 'firm-productivity effect') documented in previous studies and provide empirical evidence to existing risk-based hypotheses. Moreover, we measure the fraction of the firm-productivity effect that is attributable to mispricing- or risk-based explanations under a unified framework. We also address the robustness issues related to the firm-productivity effect.

We show that the firm-productivity effect is robust (i) after controlling for various firm characteristics and factors, (ii) across time, and (iii) using different measures of firm productivity. Our decomposition tests show that variables related to past performance and limits-to-arbitrage explain most of the firm-productivity effect, followed by those related to distress risk. However, the explanatory power of adjustment costs is low.

We find evidence of acute reversals in productive and unproductive firms' operating performance, productivity, and stock returns around the portfolio formation year. The evidence shows that investors appear to extrapolate past operating performance, stock returns, and productivity too far into the future, resulting in the overvaluation of productive firms and the undervaluation of unproductive firms. The reversal in returns concentrates around earnings announcements when value-relevant information is released, resulting in the correction of their expectation errors about the firms' future performance. Furthermore, the return predictability using firm productivity is strong in firms with large arbitrage costs, suggesting that limits-to-arbitrage hinders arbitrage trading that would otherwise push stock prices back to their fundamental values. We also find that the firm-productivity effect is stronger following periods of high investor sentiment when speculative demand is high.

Our results show that the firm productivity effect is strong amongst stocks with high investment frictions or high distress risk. Nonetheless, there is no convincing evidence that operating costs drive the firm-productivity effect. We also find that firms with unproductive firms are more sensitive to macroeconomic shocks than their productive counterparts. Exposures to macroeconomic risks explain a large part of the firm productivity effect, but the effect is persistent throughout the decades, regardless of the macroeconomic condition.

Overall, the evidence supports both mispricing- and risk-based explanations for the cross-sectional return-predictability using firm-productivity, but the results from our decomposition tests favor mispricing-based explanations.

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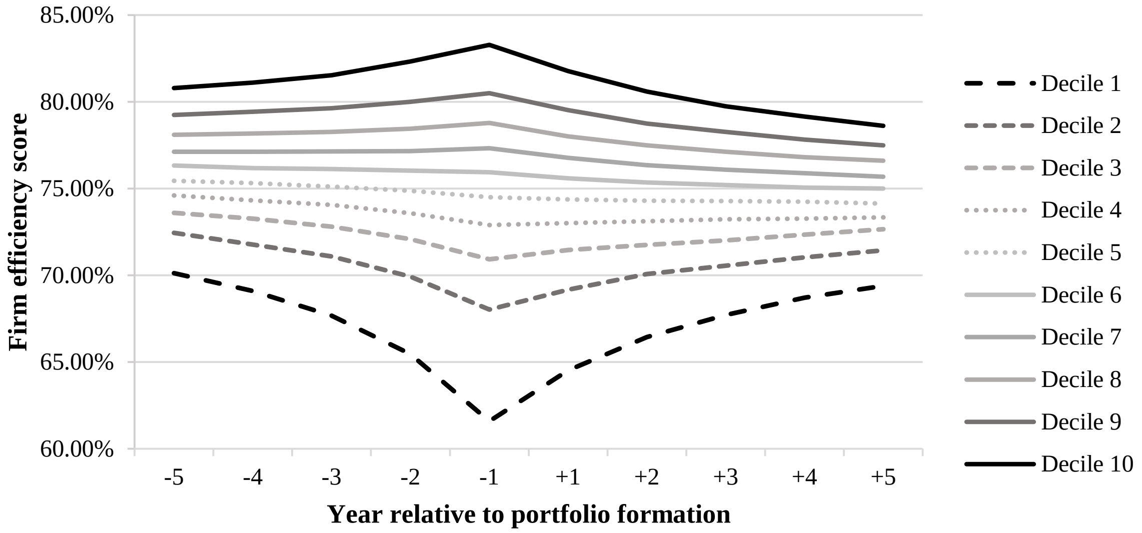
A



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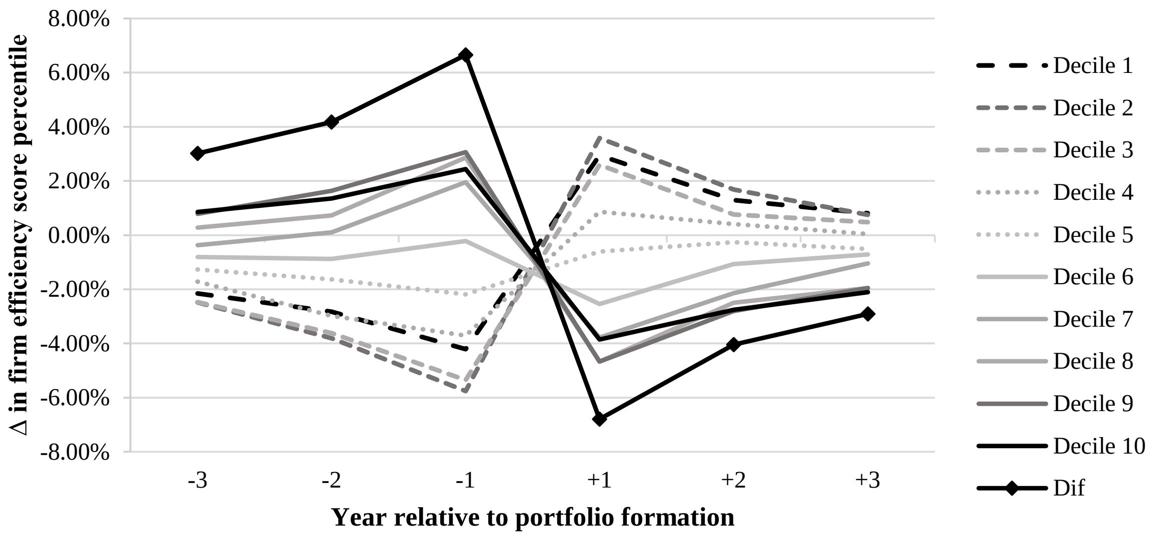
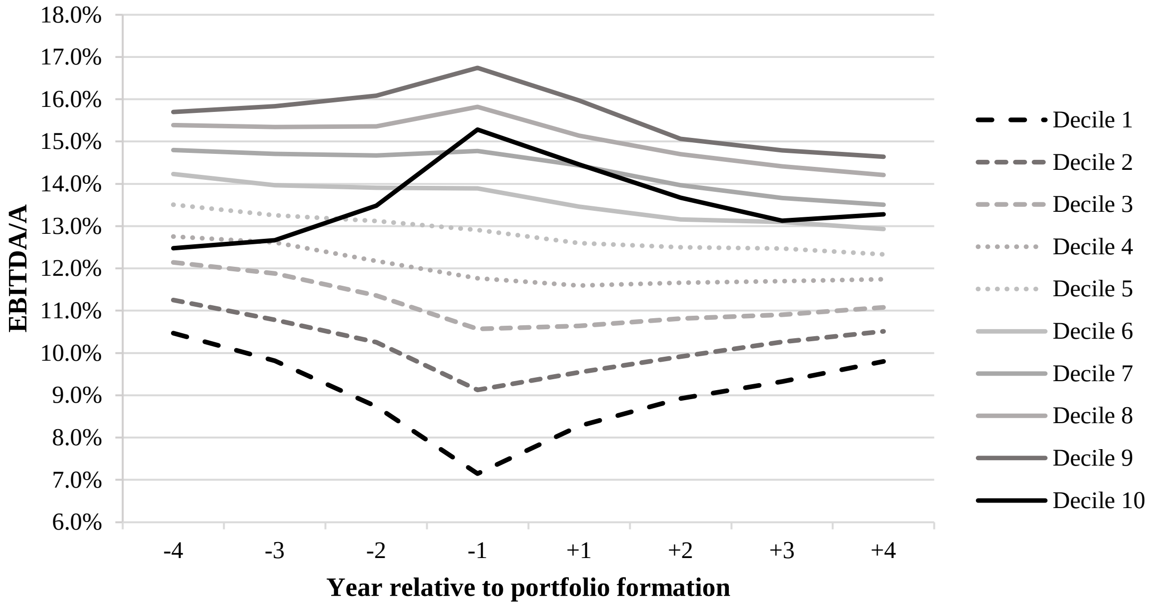


Figure 1. Mean firm productivity score and change in firm productivity score sorted by firm productivity in event time. At the end of June every year, we sort firms into 10 portfolios based on their productivity scores. Portfolio 1 has the lowest productivity, while portfolio 10 has the highest productivity. The portfolios are rebalanced every year. Panels A and B plot the time-series average of median (i) firm productivity score and (ii) change in firm productivity percentile, respectively for the firm-productivity deciles in event time. Year -1 is contemporaneous with the portfolio sorting period. Year +1 is the year following portfolio formation.

A



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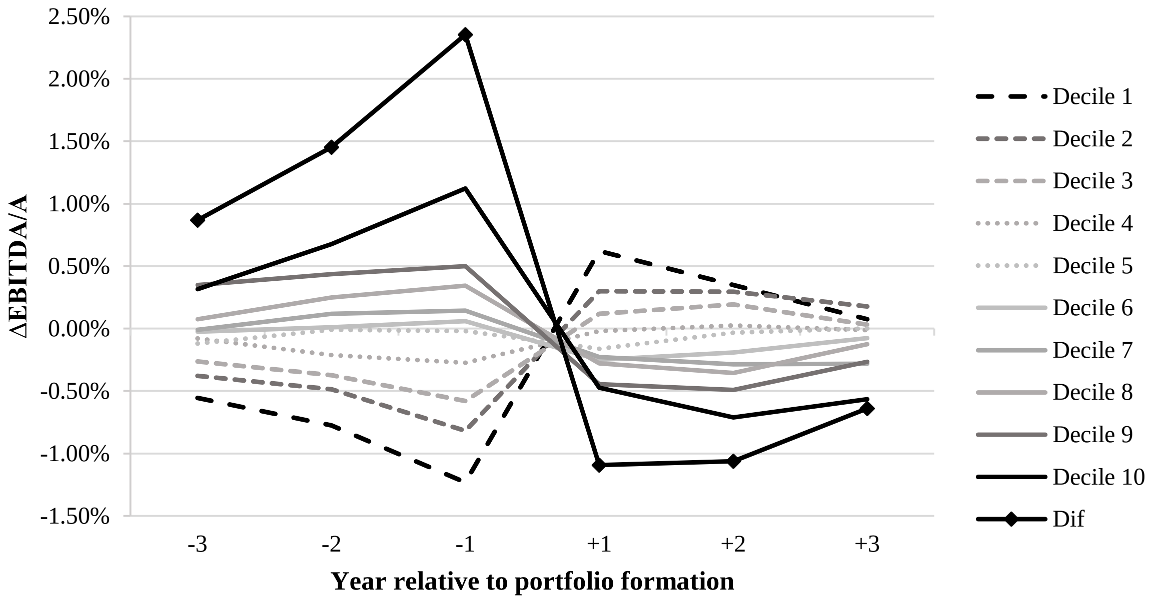

Figure 2. Mean operating performance and change in operating performance sorted by firm productivity in event time. At the end of June every year, we sort firms into 10 portfolios based on their productivity scores. Portfolio 1 has the lowest productivity, while portfolio 10 has the highest productivity. The portfolios are rebalanced every year. Panels A and B plot the time-series average of median (i) operating performance and (ii) change in operating performance, respectively for the firm-productivity deciles in event time. Year -1 is contemporaneous with the portfolio sorting period. Year +1 is the year following portfolio formation.

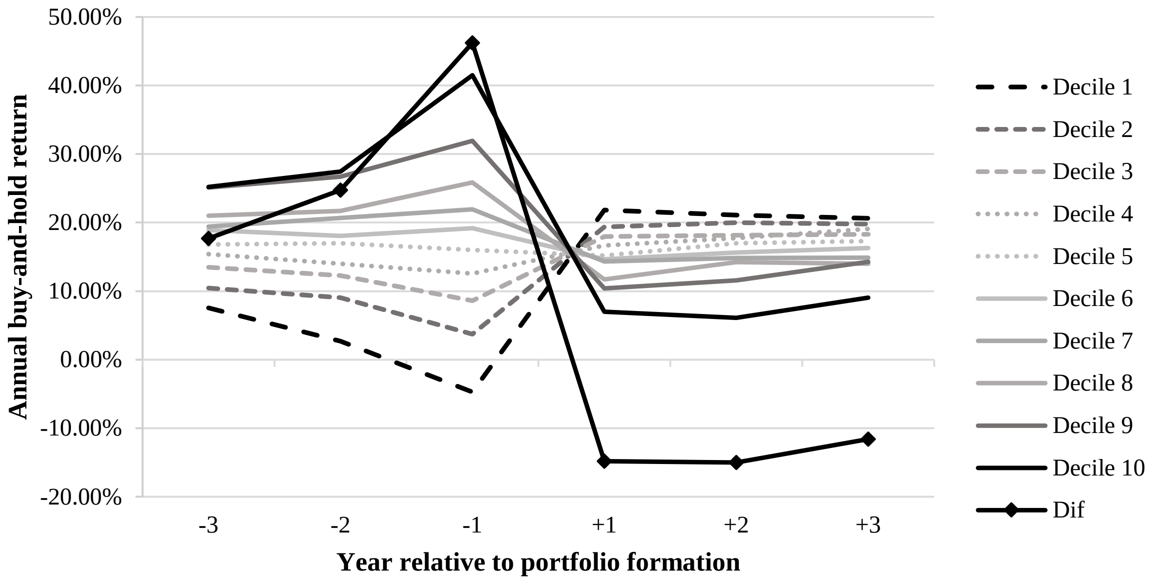

Figure 3. Mean annual buy-and-hold returns sorted by firm productivity in event time. At the end of June every year, we sort firms into 10 portfolios based on their productivity scores. Portfolio 1 has the lowest productivity, while portfolio 10 has the highest productivity. The portfolios are rebalanced every year. We plot the time-series average of equally-weighted mean annual buy-and-hold return for the firm-productivity deciles in event time. Year -1 is contemporaneous with the portfolio sorting period. Year +1 is the year following portfolio formation.

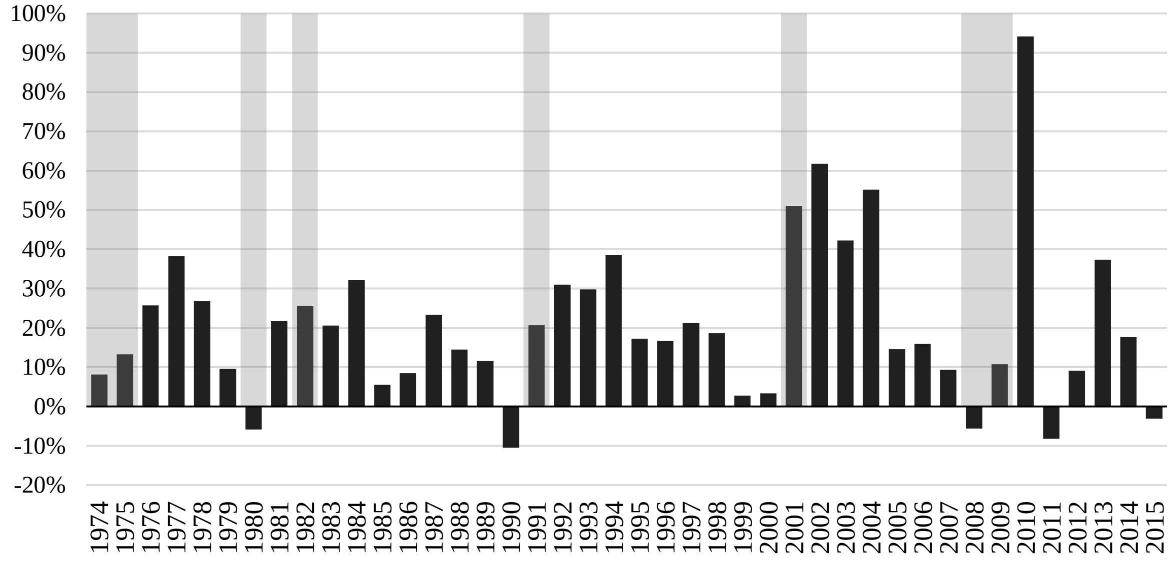

Figure 4. Annual returns to firm-productivity spread portfolio. The figure plots the annual buy-and-hold return to equally-weight firm productivity spread portfolios. The spread is the difference between the returns of portfolio with the lowest and highest firm productivity. The shaded area denotes recession years as defined by the National Bureau of Economic Research (NBER).

Table 1
Descriptive statistics

This table presents the descriptive statistics of portfolios formed based on firm productivity. At the end of June every year, we sort firms into 10 portfolios based on their firm productivity score generated from equation 2. Portfolio 1 has the lowest productivity, while portfolio 10 has the highest productivity. The portfolios are rebalanced every year and all stocks are equally-weighted within a portfolio. Each figure represents the time-series average of yearly median portfolio characteristics. The variables are firm-productivity score (Eff), total-factor productivity (TFP), mean past three-year change in EFF (PΔEFF), market capitalization (Size), firm age (AGE), beta (β), mispricing score (MISP), previous-month return (PRET), past six-month return (MOM), past three-year return (PYRET), capital investment (IK), labor hiring (LABOR), book-to-market ratio (BM), sales growth (GS), asset growth (AG), gross profit scaled by assets (GPA), net profit scaled by assets (ROA), mean past three-year change in ROA (PΔROA), leverage (LEV), Merton's (1974) distance-to-default (DD), Ohlson's (1980) O-score (O), Altman's (1968) Z-score (Z), idiosyncratic volatility (IVOL), bid-ask spread (BASK), Amihud's (2002) price impact measure (AMI), and average daily trading volume (DVOL). All variables are defined in Appendix A. The sample period is from July 1973 through June 2015. The *t*-statistics (in parentheses) are corrected for autocorrelation using the Newey-West (1987) autocorrelation-adjusted standard error. ***, **, and * denote significance at the 1%, 5%, and 10% level respectively.

Deciles	1 (Low)	2	3	4	5	6	7	8	9	10 (High)	Dif. (10 - 1)	t-stat.
General Characteristics												
Eff	0.63	0.68	0.71	0.73	0.75	0.76	0.77	0.79	0.80	0.83	0.21	(79.79)***
TFP	-0.16	-0.12	-0.07	-0.03	0.00	0.04	0.07	0.11	0.15	0.17	0.33	(25.72)***
PΔEFF	-0.04	-0.05	-0.04	-0.03	-0.01	0.00	0.01	0.02	0.02	0.02	0.06	(18.08)***
Size	31.92	67.34	107.02	162.37	223.56	294.22	391.62	512.36	494.02	405.48	373.56	(4.36)***
AGE	9.85	10.38	10.69	11.20	11.63	11.81	11.69	11.11	9.92	7.74	-2.11	(-4.86)***
β	1.04	1.06	1.08	1.12	1.12	1.12	1.14	1.15	1.19	1.24	0.20	(4.54)***
Past returns												
PRET	-2.53	-1.50	-0.97	-0.48	-0.31	0.25	0.65	1.15	1.57	2.06	4.59	(8.01)***
MOM	-3.87	1.21	4.15	6.81	8.98	11.06	12.56	14.46	16.94	21.25	25.13	(12.47)***
PYRET	-5.68	1.26	5.38	9.43	12.56	15.55	18.19	22.09	27.71	33.89	39.57	(14.16)***

Table 1 – continued

Deciles	1 (Low)	2	3	4	5	6	7	8	9	10 (High)	Dif. (10 - 1)	t-stat.
Investment												
IK	0.19	0.21	0.21	0.22	0.22	0.23	0.24	0.25	0.28	0.32	0.13	(16.22)***
LABOR	-0.01	0.01	0.01	0.02	0.03	0.04	0.05	0.06	0.07	0.10	0.11	(18.72)***
Growth indicators												
BM	1.79	1.28	1.06	0.93	0.80	0.70	0.60	0.50	0.37	0.20	-1.59	(-19.43)***
GS	0.07	0.08	0.09	0.10	0.10	0.11	0.11	0.12	0.14	0.15	0.08	(19.35)***
AG	0.01	0.03	0.05	0.07	0.08	0.09	0.10	0.12	0.14	0.16	0.15	(13.94)***
Profitability												
GPA	0.32	0.34	0.34	0.35	0.36	0.37	0.38	0.39	0.41	0.40	0.08	(5.38)***
ROA	0.01	0.02	0.03	0.04	0.05	0.06	0.06	0.07	0.08	0.06	0.05	(20.74)***
PΔROA	-0.60	-0.48	-0.34	-0.21	-0.14	-0.06	-0.03	0.07	0.22	0.36	0.96	(8.16)***
Distress risk												
LEV	0.31	0.22	0.19	0.18	0.17	0.15	0.14	0.11	0.07	0.05	-0.26	(-16.86)***
DD	7.84	1.53	0.41	0.19	0.08	0.01	0.01	0.00	0.00	0.00	-7.84	(-4.08)***
OSCORE	-0.75	-1.09	-1.33	-1.43	-1.56	-1.66	-1.69	-1.76	-1.68	-0.32	0.42	(4.30)***
ZSCORE	-2.80	-3.06	-3.25	-3.35	-3.50	-3.65	-3.79	-4.13	-4.56	-4.55	-1.75	(-11.74)***
Adjustment cost												
OC	1.09	1.10	1.09	1.08	1.06	1.05	1.04	1.05	1.04	1.09	0.01	(0.20)
Trading costs												
IVOL	2.86	2.53	2.31	2.17	2.05	1.97	1.92	1.92	2.01	2.36	-0.50	(-4.51)***
AMI	2.22	1.95	1.47	1.19	0.88	0.66	0.52	0.38	0.24	0.21	-2.01	(-6.36)***
BASK	3.10	1.63	0.98	0.66	0.40	0.26	0.23	0.16	0.11	0.12	-2.98	(-5.17)***
DVOL	10.39	31.90	58.89	98.02	137.11	189.75	276.64	371.45	384.93	326.95	316.56	(3.81)***

Table 2
Firm-level productivity and returns: Alphas, Betas, and Fama-MacBeth regressions

At the end of June every year, we sort firms into 10 portfolios based on their firm productivity score generated from equation 2. Portfolio 1 has the lowest productivity, while portfolio 10 has the highest productivity. The portfolios are rebalanced every year and all stocks are equally-weighted within a portfolio. Portfolio returns are from July of the sorting year through June of the following year. Panel A reports the average returns and alphas from factor models. Avg. ret. refers to the time-series mean of monthly average portfolio returns. The alphas are the intercept with respect to the CAPM, Fama and French's (1993) three-factor model, Carhart's (1997) four-factor model, and Fama and French's (2015) five-factor model. Panel B presents the factor loadings from the factor models. β_{Mkt}, β_{SMB}, β_{HML}, and β_{WML} are factor loadings from Carhart's (1997) four-factor model. β_{RMW} and β_{CMA} are factor loadings from Fama and French's (2015) five-factor model. Panel C reports the time-series average coefficients from monthly cross-sectional Fama-MacBeth regressions of future realized returns on firm characteristics. Eff is the firm-productivity score, TFP is the total factor productivity, AG is asset growth, GPA is gross profit divided by total assets, LEV is leverage, Size is total market capitalization, BM is the book-to-market ratio, MOM is the return over the past six-month and PRET is past-month return. All variables are defined in Appendix A. The sample period is from July 1973 through June 2015. The *t*-statistics (in parentheses) are corrected for autocorrelation using the Newey-West (1987) autocorrelation-adjusted standard error with 12 lags. ***, **, and * denote significance at the 1%, 5%, and 10% level respectively.

Deciles	1 (Low)	2	3	4	5	6	7	8	9	10 (High)	Dif. (10 - 1)
Panel A: Average portfolio returns and alphas											
Eff measure											
Avg. ret	1.95***	1.67***	1.58***	1.49***	1.43***	1.35***	1.32***	1.11***	1.02***	0.75**	-1.20***
t-stat.	(5.74)	(5.55)	(5.48)	(5.48)	(5.41)	(5.35)	(5.16)	(4.37)	(3.71)	(2.36)	(-6.90)
CAPM α	0.91***	0.64***	0.55***	0.43**	0.38**	0.29*	0.25	0.03	-0.11	-0.42**	-1.33***
t-stat.	(3.83)	(3.14)	(2.85)	(2.48)	(2.17)	(1.90)	(1.64)	(0.23)	(-0.78)	(-2.27)	(-7.64)
FF3 α	0.51***	0.29***	0.21**	0.12*	0.10	0.04	0.04	-0.12	-0.20***	-0.45***	-0.96***
t-stat.	(3.82)	(2.97)	(2.38)	(1.77)	(1.30)	(0.59)	(0.49)	(-1.61)	(-2.82)	(-4.35)	(-7.99)
FF4 α	0.79***	0.53***	0.41***	0.30***	0.26***	0.19**	0.17**	0.01	-0.05	-0.34***	-1.13***
t-stat.	(5.46)	(4.78)	(4.02)	(3.92)	(2.81)	(2.53)	(1.99)	(0.15)	(-0.65)	(-2.94)	(-9.64)
FF5 α	0.72***	0.47***	0.33***	0.21**	0.17*	0.09	0.07	-0.05	-0.08	-0.28**	-1.00***
t-stat.	(4.16)	(3.52)	(2.85)	(2.37)	(1.75)	(1.12)	(0.74)	(-0.57)	(-0.85)	(-2.44)	(-7.08)
TFP measure											
Avg. ret	1.69***	1.71***	1.63***	1.52***	1.54***	1.43***	1.47***	1.31***	1.26***	1.16***	-0.53***
t-stat.	(4.59)	(5.63)	(5.77)	(5.61)	(5.91)	(5.69)	(6.05)	(5.55)	(5.42)	(4.57)	(-2.70)
FF5 α	0.56***	0.44***	0.30***	0.12	0.14	0.03	0.12	-0.02	0.01	0.05	-0.51***
t-stat.	(2.86)	(3.08)	(2.67)	(1.23)	(1.49)	(0.36)	(1.25)	(-0.21)	(0.15)	(0.55)	(-3.18)

Table 2 - continued

Deciles	1 (Low)	2	3	4	5	6	7	8	9	10 (High)	Dif. (10 - 1)
Panel B: Factor loadings											
β_{Mkt}	0.91***	0.92***	0.95***	0.99***	0.98***	1.01***	1.03***	1.03***	1.08***	1.12***	0.20***
t-stat.	(27.76)	(34.30)	(34.42)	(41.20)	(48.51)	(38.14)	(42.89)	(39.95)	(48.66)	(46.74)	(6.51)
β_{SMB}	1.21***	1.14***	1.02***	0.99***	0.90***	0.86***	0.80***	0.74***	0.76***	0.85***	-0.36***
t-stat.	(19.34)	(29.64)	(18.23)	(22.69)	(17.95)	(15.52)	(11.04)	(8.80)	(11.37)	(13.57)	(-5.01)
β_{HML}	0.35***	0.25***	0.30***	0.26***	0.23***	0.18***	0.13**	0.02	-0.12**	-0.27***	-0.62***
t-stat.	(4.34)	(4.80)	(5.70)	(5.84)	(4.72)	(3.35)	(2.17)	(0.32)	(-2.35)	(-4.85)	(-9.96)
β_{WML}	-0.32***	-0.28***	-0.23***	-0.21***	-0.18***	-0.18***	-0.15***	-0.15***	-0.17***	-0.13***	0.19***
t-stat.	(-5.18)	(-4.89)	(-4.54)	(-5.01)	(-4.73)	(-4.95)	(-3.65)	(-3.41)	(-3.91)	(-2.84)	(4.80)
β_{RMW}	-0.38***	-0.32***	-0.16**	-0.14**	-0.08	-0.04	0.02	-0.03	-0.13*	-0.29***	0.09
t-stat.	(-3.66)	(-4.33)	(-2.21)	(-2.02)	(-1.24)	(-0.57)	(0.28)	(-0.32)	(-1.70)	(-3.85)	(0.94)
β_{CMA}	-0.16	-0.15	-0.17	-0.08	-0.08	-0.07	-0.09	-0.17	-0.25**	-0.20*	-0.04
t-stat.	(-0.71)	(-0.82)	(-0.94)	(-0.53)	(-0.72)	(-0.62)	(-0.97)	(-1.38)	(-2.00)	(-1.92)	(-0.26)

Table 2 - continued

Panel C: Fama-MacBeth regressions									
	Models								
	1	2	3	4	5	6	7	8	9
Int	4.994***	1.355***	5.079***	1.724***	4.388***	2.061***	4.661***	4.412***	4.587***
	(7.02)	(5.60)	(6.33)	(4.02)	(4.37)	(5.06)	(4.72)	(4.40)	(4.52)
Eff	-4.886***		-4.950***		-3.894***		-4.222***	-4.238***	-4.031***
	(-6.17)		(-5.28)		(-3.52)		(-3.88)	(-3.94)	(-3.58)
TFP		-0.393***	-0.204			0.087			
		(-2.76)	(-1.58)			(0.95)			
AG							-0.361***		
							(-5.60)		
GPA								0.548***	
								(3.10)	
LEV									-0.477*
									(-1.67)
Ln(SIZE)				-0.056	-0.030	-0.101**	-0.028	-0.028	-0.028
				(-1.27)	(-0.71)	(-2.55)	(-0.66)	(-0.67)	(-0.65)
LN(BM)				0.304***	0.098	0.280***	0.024	0.083	0.129
				(3.61)	(0.79)	(3.53)	(0.20)	(0.67)	(1.12)
MOM				0.318**	0.475***	0.343**	0.481***	0.471***	0.484***
				(2.15)	(3.05)	(2.26)	(3.05)	(3.07)	(3.08)
PRET				-0.049***	-0.049***	-0.053***	-0.049***	-0.050***	-0.050***
				(-8.18)	(-8.18)	(-8.83)	(-8.23)	(-8.26)	(-8.38)
Adj. R^2 (%)	0.37	0.45	0.90	2.64	2.81	2.90	2.91	3.08	3.00

Table 3
Past performance, firm productivity, and returns: Event time analysis

Panel A reports the pre- and post-event equally-weighted three-year average change in productivity score percentile of unproductive (decile 1) and productive firms (decile 10), as well as their differences. Panel B shows the three-year average change in operating performance. Panel C reports the three-year average annual buy-and-hold return. The sample period is from July 1973 through June 2015. The *t*-statistics (in parentheses) are corrected for autocorrelation using the Newey-West (1987) autocorrelation-adjusted standard error with 3 lags. ***, **, and * denote significance at the 1%, 5%, and 10% level respectively.

Panel A: Pre- and post-event change in productivity score percentile				
		Unproductive	Productive	Dif.
Pre-formation	Avg.	-3.06***	1.55***	4.61***
	t-stat.	(-25.11)	(18.33)	(24.42)
Post-formation	Avg.	1.68***	-2.90***	-4.58***
	t-stat.	(20.25)	(-19.26)	(-24.07)
Dif.	Avg.	4.74***	-4.45***	-9.19***
	t-stat.	(29.36)	(-23.53)	(-33.69)

Panel B: Pre- and post-event operating performance				
		Unproductive	Productive	Dif.
Pre-formation	Avg.	-0.85***	0.70***	1.56***
	t-stat.	(-11.81)	(10.36)	(16.31)
Post-formation	Avg.	0.35***	-0.58***	-0.93***
	t-stat.	(6.38)	(-9.22)	(-15.47)
Dif.	Avg.	1.20***	-1.28***	-2.49***
	t-stat.	(12.14)	(-12.56)	(-18.98)

Panel C: Pre- and post-event annual buy-and-hold return				
		Unproductive	Productive	Dif.
Pre-formation	Avg.	1.83***	31.38***	29.55***
	t-stat.	(4.89)	(13.92)	(18.49)
Post-formation	Avg.	21.18***	7.39***	-13.79***
	t-stat.	(8.65)	(4.16)	(-7.92)
Dif.	Avg.	19.35***	-23.99***	-43.34***
	t-stat.	(9.51)	(-8.06)	(18.30)

Table 4
Earnings announcement returns

At the end of June every year, we sort firms into 10 portfolios based on their firm productivity score generated from equation 2. Portfolio 1 has the lowest productivity, while portfolio 10 has the highest productivity. The portfolios are rebalanced every year and all stocks are equally-weighted within a portfolio. Panel A reports the average earnings announcement returns and non-announcement returns from July of the sorting year through June of the following year. *Ann. Ret* is the average daily return over the 3-day window surrounding earnings announcements. *Non-ann. Ret* is the average daily return for other days outside earnings announcement periods. Panel B presents the average annual buy-and-hold return (BHRET). The sample is from July 1973 through June 2015. ***, **, and * denote significance at the 1%, 5%, and 10% level respectively.

Decile	1 (Low)	2	3	4	5	6	7	8	9	10 (High)	Dif.	t-stats
Panel A: Average daily return - earnings announcement period versus non-earnings announcement period												
Ann. Ret (%)	0.341	0.272	0.203	0.175	0.150	0.147	0.144	0.099	0.069	-0.009	-0.350	(-6.91)***
Non-ann. Ret (%)	0.163	0.115	0.104	0.094	0.084	0.081	0.075	0.068	0.070	0.067	-0.096	(-9.25)***
Dif. (%)	0.178	0.157	0.099	0.081	0.065	0.067	0.069	0.032	-0.001	-0.076	-0.254	(-5.56)***
t-stats	(4.38)***	(4.51)***	(4.22)***	(4.14)***	(2.77)***	(3.10)***	(3.37)***	(1.71)*	(-0.04)	(-2.34)**		
Panel B: Annual buy-and-hold return												
BHRET	23.1	20.5	19.0	17.7	16.1	15.8	15.4	12.8	11.5	8.1	-15.0	
t-stats	(4.97)***	(5.17)***	(4.86)***	(4.93)***	(4.82)***	(4.59)***	(4.42)***	(3.91)***	(3.33)***	(2.05)**	(-5.60)***	

Table 5
Limits-to-arbitrage, firm productivity, and returns

Panels A to D report the equally-weighted average monthly returns for portfolios independently sorted on a measure of limit-to-arbitrage (Arb) and firm productivity (Eff). The portfolios are rebalanced every year. IVOL is idiosyncratic volatility, BASK is the bid-ask spread, AMI is Amihud's (2002) illiquidity measure, and DVOL is the average daily dollar trading volume. Panel E presents the time-series means of the coefficients from monthly cross-sectional Fama-MacBeth regressions of future realized returns on firm characteristics. The dependent variable is individual stock's monthly return from July year *t* to June year *t+1*. *Arb* denotes the proxy for limits-to-arbitrage. All variables are defined in Appendix A. The *t*-statistics (in parentheses) are corrected for autocorrelation using the Newey-West (1987) autocorrelation-adjusted standard error with 12 lags. ***, **, and * denote significance at the 1%, 5%, and 10% level respectively.

Panel A: Idiosyncratic volatility and firm productivity

	IVOL				
Firm Eff.	1 (Low)	2	3	4	5 (High)
1 (Low)	1.35	1.68	1.65	1.93	1.79
2	1.34	1.53	1.64	1.64	1.14
3	1.30	1.46	1.51	1.29	0.97
4	1.26	1.31	1.33	1.06	0.75
5 (High)	1.05	1.18	1.12	0.82	0.03
Dif. (5 - 1)	-0.30*	-0.51***	-0.53***	-1.11***	-1.75***
t-stat.	(-1.88)	(-3.10)	(-2.74)	(-6.49)	(-9.63)

Panel B: Bid-ask spread

	BASK				
Firm Eff.	1 (Low)	2	3	4	5 (High)
1 (Low)	1.49	1.51	1.75	1.71	1.97
2	1.40	1.48	1.53	1.57	1.53
3	1.22	1.43	1.44	1.41	1.25
4	1.20	1.26	1.20	1.14	1.07
5 (High)	0.84	1.05	1.06	1.08	0.46
Dif. (5 - 1)	-0.65***	-0.43**	-0.68***	-0.63***	-1.51***
t-stat.	(-3.81)	(-2.51)	(-3.60)	(-3.16)	(-7.07)

Table 5 – continued

Panel C: Price impact and firm productivity					
	AMI				
Firm Eff.	1 (Low)	2	3	4	5 (High)
1 (Low)	1.26	1.10	1.52	1.73	2.08
2	1.30	1.30	1.48	1.51	1.81
3	1.17	1.33	1.38	1.40	1.60
4	1.10	1.17	1.20	1.21	1.26
5 (High)	0.97	0.92	0.82	0.75	0.92
Dif. (5 - 1)	-0.28	-0.18	-0.70***	-0.98***	-1.16***
t-stat.	(-1.39)	(-1.01)	(-3.92)	(-5.46)	(-5.92)

Panel D: Trading volume and firm productivity					
	DVOL				
Firm Eff.	1 (Low)	2	3	4	5 (High)
1 (Low)	2.01	1.81	1.44	1.20	1.14
2	1.75	1.61	1.39	1.32	1.28
3	1.56	1.42	1.44	1.29	1.12
4	1.25	1.30	1.15	1.19	1.06
5 (High)	0.94	0.90	0.82	0.83	0.96
Dif. (5 - 1)	-1.08***	-0.91***	-0.63***	-0.37*	-0.18
t-stat.	(-5.97)	(-5.20)	(-3.53)	(-1.93)	(-0.89)

Table 5 – continued

Panel E: Fama-MacBeth regressions										
		Int	Eff	Arb	Eff*Arb	Ln(SIZE)	Ln(BM)	MOM	PRET	Adj R^2 (%)
IVOL	Model 1	4.984***	-4.300***	-0.114***		-0.053	0.045	0.643***	-0.051***	3.503
		(6.21)	(-4.15)	(-2.76)		(-1.56)	(0.37)	(3.51)	(-7.90)	
	Model 2	2.237**	-0.378	0.786***	-1.250***	-0.074**	0.051	0.656***	-0.051***	3.605
		(2.39)	(-0.30)	(5.27)	(-6.02)	(-2.17)	(0.42)	(3.57)	(-7.88)	
BASK	Model 3	4.596***	-4.057***	-0.054		-0.035	0.077	0.628***	-0.054***	3.756
		(6.57)	(-4.05)	(-0.63)		(-0.90)	(0.67)	(3.41)	(-8.37)	
	Model 4	2.441***	-0.952	0.693***	-1.047***	-0.051	0.057	0.672***	-0.054***	3.846
		(2.65)	(-0.68)	(3.04)	(-3.33)	(-1.30)	(0.50)	(3.68)	(-8.35)	
AMI	Model 5	4.100***	-3.749***	1.988**		-0.001	0.104	0.592***	-0.053***	3.397
		(3.99)	(-3.20)	(2.47)		(-0.02)	(0.76)	(3.00)	(-7.84)	
	Model 6	4.268***	-3.984***	3.242	-1.904	0.002	0.100	0.594***	-0.053***	3.467
		(4.07)	(-3.29)	(0.76)	(-0.32)	(0.05)	(0.73)	(2.98)	(-7.83)	
DVOL	Model 7	4.248***	-3.795***	-0.000**		-0.010	0.120	0.606***	-0.053***	3.319
		(4.17)	(-3.37)	(-2.09)		(-0.22)	(0.89)	(3.05)	(-7.78)	
	Model 8	4.360***	-3.968***	-0.000	0.000	-0.006	0.120	0.608***	-0.053***	3.356
		(4.34)	(-3.57)	(-1.17)	(0.92)	(-0.12)	(0.89)	(3.04)	(-7.80)	

Table 6
Investor sentiment, firm productivity, and returns

The table reports the average portfolios returns sorted on firm productivity, conditioned on market sentiment as defined by Baker and Wurgler (2006). Firm productivity (Eff) is generated from equation 2. A high-sentiment (low-sentiment) month is one in which the value of Baker and Wurgler's sentiment index in the previous month is above (below) the median value of the sample period. The sample period is from July 1973 through June 2015. The *t*-statistics (in parentheses) are corrected for autocorrelation using the Newey-West (1987) autocorrelation-adjusted standard error with 12 lags. ***, **, and * denote significance at the 1%, 5%, and 10% level respectively.

Deciles	1 (Low)	2	3	4	5	6	7	8	9	10 (High)	Dif. (10 - 1)
Panel B: Average portfolio returns, conditioned on investor sentiment											
Low investor sentiment											
Avg. ret	2.35***	2.01***	1.93***	1.74***	1.75***	1.62***	1.69***	1.50***	1.50***	1.44***	-0.92***
t-stat.	(4.84)	(4.44)	(4.51)	(4.06)	(4.25)	(3.99)	(4.15)	(3.82)	(3.65)	(3.27)	(-4.29)
High investor sentiment											
Avg. ret	1.54***	1.33***	1.24***	1.23***	1.11***	1.08***	0.95***	0.72*	0.54	0.07	-1.47***
t-stat.	(3.92)	(3.52)	(3.39)	(3.42)	(3.15)	(3.00)	(2.68)	(1.93)	(1.35)	(0.15)	(-6.57)
Dif. (High - Low)											
Avg. ret	-0.81	-0.68	-0.69	-0.51	-0.64	-0.54	-0.74*	-0.75*	-0.96**	-1.37***	-0.56**
t-stat.	(-1.59)	(-1.44)	(-1.54)	(-1.20)	(-1.52)	(-1.32)	(-1.73)	(-1.82)	(-2.06)	(-2.62)	(-2.04)

Table 7
Adjustment costs, firm productivity, and returns

Panels A and B report the equally-weighted average monthly returns for portfolios independently sorted on a measure of adjustment cost and firm productivity. Portfolio returns are from July of the sorting year through June of the following year. The portfolios are rebalanced every year. We measure adjustment costs as investment frictions (FRISC) and operating cost (OC). FRISC is a composite score generated from the average percentile rank of firm age, total assets, and payout ratio. Operating cost (OC) is the sum of cost of goods sold and selling, general and administrative expense scaled by total assets. Panel C reports the time-series means of the coefficients from monthly cross-sectional Fama-MacBeth regressions of future realized returns on firm characteristics. The dependent variable is individual stock's monthly return from July year t to June year $t+1$. *ACOST* denotes the proxy for adjustment cost. The sample period is from July 1973 through June 2015. The t-statistics (in parentheses) are corrected for autocorrelation using the Newey-West (1987) autocorrelation-adjusted standard error with 12 lags. ***, **, and * denote significance at the 1%, 5%, and 10% level respectively.

Panel A: Investment friction and firm productivity

	Investment frictions (FRISC)				
Firm Eff.	1 (Low)	2	3	4	5 (High)
1 (Low)	1.31	1.59	1.79	1.90	2.19
2	1.46	1.50	1.48	1.49	1.75
3	1.34	1.45	1.41	1.30	1.43
4	1.23	1.37	1.12	1.20	1.17
5 (High)	1.09	1.01	1.02	0.93	0.64
Dif. (5- 1)	-0.22	-0.58***	-0.77***	-0.98***	-1.56***
t-stat.	(-1.19)	(-3.44)	(-4.84)	(-5.53)	(-8.14)

Panel B: Operating cost and firm productivity

	Operating cost (OC)				
Firm Eff.	1 (Low)	2	3	4	5 (High)
1 (Low)	1.40	1.85	1.88	1.87	1.97
2	1.16	1.61	1.67	1.59	1.61
3	1.11	1.34	1.37	1.54	1.54
4	0.99	1.25	1.20	1.23	1.43
5 (High)	0.66	0.95	0.78	0.91	1.09
Dif. (5- 1)	-0.74***	-0.90***	-1.10***	-0.96***	-0.88***
t-stat.	(-4.14)	(-5.13)	(-6.50)	(-5.07)	(-4.87)

Table 7 – continued

Panel C: Fama-McBeth regressions										
		Intercept	Eff	ACOST	Eff*ACOST	Ln(SIZE)	LN(BM)	MOM	PRET	Adj R^2 (%)
FRISC	Model 1	4.740***	-4.122***	-0.002		-0.049	0.064	0.625***	-0.052***	3.075
		(5.89)	(-3.70)	(-0.68)		(-1.24)	(0.61)	(3.38)	(-8.05)	
	Model 2	-0.165	2.591**	0.092***	-0.128***	-0.070*	0.031	0.686***	-0.052***	3.185
		(-0.16)	(1.98)	(5.43)	(-5.98)	(-1.80)	(0.29)	(3.68)	(-8.05)	
OC	Model 3	4.272***	-3.977***	0.105***		-0.023	0.091	0.485***	-0.048***	2.931
		(4.93)	(-4.12)	(3.10)		(-0.60)	(0.97)	(3.81)	(-11.32)	
	Model 4	4.351***	-4.074***	0.129	-0.039	-0.024	0.090	0.488***	-0.048***	2.961
		(4.66)	(-3.90)	(0.58)	(-0.13)	(-0.61)	(0.96)	(3.83)	(-11.33)	

Table 8
Distress risk, firm productivity, and returns

Panels A to C report the equally-weighted average monthly returns for portfolios independently sorted on distress risk and firm productivity. We use Merton's (1974) distance-to-default (DD), Ohlson's (1980) O-score (O), and Altman's (1968) Z-score (Z) as proxies for distress risk. Portfolio returns are from July of the sorting year through June of the following year. The portfolios are rebalanced every year. Panel D reports the time-series means of the coefficients from monthly cross-sectional Fama-MacBeth regressions of future realized returns on firm characteristics. The dependent variable is individual stock's monthly return from July year *t* to June year *t+1*. *Dis* denotes the proxy for distress risk. The sample period is from July 1973 through June 2015. The *t*-statistics (in parentheses) are corrected for autocorrelation using the Newey-West (1987) autocorrelation-adjusted standard error with 12 lags. ***, **, and * denote significance at the 1%, 5%, and 10% level respectively.

Panel A: Distance-to-default and firm productivity

	Distance-to-default (DD)				
Firm Eff.	1 (Low)	2	3	4	5 (High)
1 (Low)	1.58	1.62	1.70	1.82	1.84
2	1.39	1.60	1.58	1.57	1.47
3	1.38	1.42	1.41	1.25	1.29
4	1.29	1.21	1.24	1.08	1.14
5 (High)	1.03	0.95	0.79	0.67	0.76
Dif. (10 - 1)	-0.55***	-0.67***	-0.91***	-1.15***	-1.08***
t-stat.	(-2.91)	(-4.87)	(-5.08)	(-6.81)	(-5.52)

Panel B: O-score and firm productivity

	O-score (O)				
Firm Eff.	1 (Low)	2	3	4	5 (High)
1 (Low)	1.68	1.86	1.80	1.88	1.95
2	1.47	1.62	1.54	1.61	1.50
3	1.41	1.41	1.44	1.47	1.41
4	1.23	1.24	1.27	1.33	1.21
5 (High)	0.98	1.09	1.11	1.12	0.65
Dif. (10 - 1)	-0.70***	-0.77***	-0.69***	-0.76***	-1.29***
t-stat.	(-4.02)	(-4.40)	(-3.70)	(-3.72)	(-7.06)

Panel C: Z-score and firm productivity

	Z-score (Z)				
Firm Eff.	1 (Low)	2	3	4	5 (High)
1 (Low)	1.53	1.79	1.83	1.87	1.83
2	1.45	1.49	1.61	1.59	1.47
3	1.20	1.43	1.45	1.36	1.38
4	1.08	1.21	1.29	1.16	1.33
5 (High)	0.72	1.07	1.03	0.94	0.77
Dif. (10 - 1)	-0.82***	-0.72***	-0.80***	-0.93***	-1.06***
t-stat.	(-4.54)	(-4.16)	(-4.74)	(-5.61)	(-5.84)

Table 8 – continued

Panel D: Fama-McBeth regressions

		Int	Eff	Dis	Eff*Dis	Ln(SIZE)	Ln(BM)	MOM	PRET	Adj R^2 (%)
DD	Model 1	4.470***	-3.931***	-1.195**		-0.036	0.101	0.455***	-0.048***	3.195
		(4.80)	(-3.62)	(-2.32)		(-0.87)	(0.82)	(3.06)	(-7.82)	
	Model 2	4.652***	-4.186***	-1.795*	0.638	-0.034	0.096	0.461***	-0.048***	3.300
		(4.67)	(-3.61)	(-1.69)	(0.34)	(-0.84)	(0.78)	(3.07)	(-7.81)	
O	Model 3	4.654***	-4.173***	-0.028*		-0.049	0.039	0.480***	-0.049***	3.016
		(4.80)	(-3.87)	(-1.74)		(-1.32)	(0.33)	(2.91)	(-8.44)	
	Model 4	4.881***	-4.441***	0.274***	-0.402***	-0.055	0.026	0.486***	-0.049***	3.096
		(4.81)	(-3.95)	(2.75)	(-3.24)	(-1.47)	(0.21)	(2.96)	(-8.45)	
Z	Model 5	4.545***	-4.046***	-0.010***		-0.030	0.079	0.467***	-0.049***	2.942
		(4.44)	(-3.58)	(-2.91)		(-0.71)	(0.64)	(2.95)	(-8.15)	
	Model 6	4.680***	-4.182***	0.074	-0.076	-0.031	0.078	0.465***	-0.049***	3.012
		(4.21)	(-3.46)	(1.34)	(-1.17)	(-0.72)	(0.63)	(2.95)	(-8.16)	

Table 9
Macroeconomic risk, firm productivity, and returns

This table reports the alphas and factor loadings with respect to Chen, Roll, and Ross' (1986) factor model. We create CRR's macroeconomic risk mimicking portfolios based on 40 test portfolios: 4 x 10 equally-weighted portfolios sorted on size, book-to-market, momentum, and firm-productivity, respectively. β_{DEI}, β_{MP}, β_{UI}, β_{URP}, and β_{UTS} refer to the factor sensitivity to the change in expected inflation (DEI), the growth rate in industrial production (MP), unanticipated changes in inflation (UI), risk premium (URP), and the term structure (UTS), respectively. At the end of June every year, we sort firms into 10 portfolios based on their firm productivity score generated from equation 2. Portfolio 1 has the lowest productivity, while portfolio 10 has the highest productivity. All stocks are equally-weighted within a portfolio. Portfolio returns are from July of the sorting year through June of the following year and the portfolios are rebalanced every year. The sample period is from July 1973 through June 2015. The *t*-statistics (in parentheses) are corrected for autocorrelation using the Newey-West (1987) autocorrelation-adjusted standard error with 12 lags. ***, **, and * denote significance at the 1%, 5%, and 10% level respectively.

Deciles	1 (Low)	2	3	4	5	6	7	8	9	10 (High)	Dif. (10 - 1)
α	0.20***	0.15***	0.08	0.03	0.06	0.02	0.06	-0.03	-0.08	-0.36***	-0.56***
t-stat.	(4.18)	(3.01)	(1.57)	(0.72)	(1.12)	(0.51)	(1.31)	(-0.61)	(-1.39)	(-6.55)	(-8.03)
β_{DEI}	4.91***	4.36***	3.87***	3.83***	3.66***	3.60***	3.69***	4.08***	4.84***	6.88***	1.97***
t-stat.	(21.26)	(11.87)	(35.62)	(22.85)	(30.35)	(31.39)	(27.21)	(25.90)	(29.91)	(35.29)	(7.97)
β_{MP}	0.78***	0.66***	0.61***	0.57***	0.49***	0.45***	0.41***	0.33***	0.30***	0.36***	-0.42***
t-stat.	(43.48)	(22.16)	(39.54)	(33.90)	(30.99)	(38.59)	(20.40)	(20.13)	(13.70)	(17.98)	(-23.86)
β_{UI}	0.18***	-0.28***	-0.56***	-0.82***	-1.01***	-1.16***	-1.33***	-1.43***	-1.61***	-1.70***	-1.88***
t-stat.	(3.59)	(-4.50)	(-10.92)	(-25.06)	(-20.42)	(-27.92)	(-30.76)	(-25.79)	(-47.09)	(-23.84)	(-22.88)
β_{URP}	1.41***	1.40***	1.31***	1.29***	1.21***	1.19***	1.15***	1.09***	1.10***	1.09***	-0.32***
t-stat.	(71.78)	(34.87)	(43.86)	(54.40)	(57.00)	(67.66)	(55.88)	(36.76)	(52.88)	(25.96)	(-7.41)
β_{UTS}	0.65***	0.56***	0.53***	0.51***	0.47***	0.46***	0.44***	0.42***	0.43***	0.43***	-0.22***
t-stat.	(79.15)	(36.21)	(55.44)	(40.50)	(64.65)	(65.42)	(53.09)	(39.81)	(44.17)	(35.82)	(-18.31)

Table 10
Decomposing the firm-productivity effect

There are four stages in the decomposition of the firm-productivity effect. In Stage 1, we regress adjusted returns on firm productivity (Eff). In Stage 2, we add a candidate variable to the cross-sectional regressions, in turn. In Stage 3, we regress firm productivity on a candidate variable, in turn. In Stage 4, we decompose the estimated coefficient in Stage 1 into two parts: the fraction explained by the candidate variable and the fraction left unexplained. Panel A to C report the results of the univariate analysis. PYRET is mean past three-year annual return, P∆ROA is past three-year mean yearly change in earnings scaled by total assets, P∆EFF is the past three-year mean yearly change in Eff, IVOL is idiosyncratic volatility, BASK is the bid-ask spread, AMI is Amihud's (2002) price impact measure, DVOL is average daily trading volume, FRISC is the composite score for investment frictions, OC is operating cost DD is Merton's (1974) distance-to-default measure, O is Ohlson's (1980) O-score, and Z is Altman's (1968) Z-score. Panel D presents the results of the multivariate analysis. All variables are defined in Appendix A. The sample period is from July 1973 through June 2015. The *t*-statistics are in parentheses. The standard errors of the fractions are determined using the multivariate delta method. ***, **, and * denote significance at the 1%, 5%, and 10% level respectively.

Panel A: Variables related to past performance								
Stage	Description	Variable	Models					
			1. PYRET		2. P∆ROA		3. P∆EFF	
1	Adj. ret. on Eff	Intercept	0.821***	(2.87)	1.991***	(7.16)	0.835***	(2.89)
		Eff	-1.068***	(-2.72)	-2.468***	(-6.51)	-1.071***	(-2.70)
2	Adj. ret. on Eff	Intercept	0.413	(1.13)	2.020***	(7.77)	0.745**	(2.57)
	and candidate	Eff	-1.539***	(-3.03)	-2.501***	(-7.06)	-0.947**	(-2.41)
		Candidate	-0.126	(-0.76)	0.003	(0.33)	-0.059	(-0.17)
3	Eff on candidate	Intercept	0.731***	(356.03)	0.743***	(446.20)	0.745***	(460.31)
		Candidate	0.077***	(22.21)	0.001***	(5.85)	0.273***	(76.69)
		Adj R^2 (%)	13.925		0.877		16.469	
4	Decompose	Candidate	-0.266		-0.081		-0.328	
	Stage 1 coef.		24.90%*	(1.89)	3.28%**	(2.21)	30.62%**	(2.46)
		Residual	-0.802		-2.387		-0.743	
			75.10%***	(3.66)	96.72%***	(17.71)	69.38%***	(4.30)
	Avg # /mth		2816		2282		2599	

Table 10 – continued

Panel B: Variables related to limits-to-arbitrage										
Stage	Description	Variable	Models							
			4. IVOL		5. BASK		6. AMI		7. DVOL	
1	Adj. ret. on Eff	Intercept	1.008***	(3.79)	1.009***	(3.79)	0.910***	(3.27)	0.910***	(3.27)
		Eff	-1.346***	(-3.73)	-1.348***	(-3.73)	-1.215***	(-3.22)	-1.215***	(-3.22)
2	Adj. ret. on Eff	Intercept	1.200***	(5.23)	0.915***	(4.35)	0.693**	(2.20)	0.943***	(2.78)
	and candidate	Eff	-1.373***	(-4.47)	-1.198***	(-3.69)	-0.946**	(-2.26)	-1.264***	(-2.67)
		Candidate	-0.096***	(-3.11)	-0.029	(-0.48)	1.437**	(2.09)	-0.000	(-0.63)
3	Eff on candidate	Intercept	0.757***	(491.83)	0.750***	(400.43)	0.750***	(417.70)	0.739***	(430.59)
		Candidate	-0.005***	(-11.18)	-0.002***	(-2.93)	-0.235***	(-7.48)	0.000***	(3.89)
		Adj R^2 (%)	2.406		0.773		5.646		4.929	
4	Decompose	Candidate	-0.199		-0.189		-0.046		0.062	
	Stage 1 coef.		14.78%*	(1.81)	14.05%***	(2.71)	3.79%	(0.34)	-5.07%	(-0.75)
		Residual	-1.147		-1.158		-1.169		-1.276	
			85.22%***	(6.99)	85.95%***	(8.35)	96.21%***	(7.71)	105.07%***	(9.46)
	Avg # /mth		3106		3106		2854		2854	

Table 10 – continued

Panel C: Variables related to risk												
Stage	Description	Variable	Models									
			8. FRISC		9. OC		10. DD		11. O		12. Z	
1	Adj. ret. on Eff	Intercept	0.945***	(3.18)	0.945***	(3.70)	0.835***	(2.99)	0.952***	(3.26)	1.056***	(3.68)
		Eff	-1.270***	(-3.13)	-1.279***	(-3.66)	-1.137***	(-2.95)	-1.234***	(-3.09)	-1.414***	(-3.61)
2	Adj. ret. on Eff	Intercept	1.022***	(4.47)	0.803***	(2.81)	1.171***	(3.01)	0.934***	(3.10)	1.030***	(3.29)
	and candidate	Eff	-1.264***	(-3.12)	-1.231***	(-3.56)	-1.562***	(-3.04)	-1.267***	(-3.16)	-1.325***	(-3.03)
		Candidate	-0.002	(-0.61)	0.095*	(1.67)	-1.232**	(-2.51)	-0.034**	(-2.01)	0.011	(1.29)
3	Eff on candidate	Intercept	0.745***	(314.46)	0.743***	(394.72)	0.751***	(469.55)	0.742***	(475.07)	0.734***	(671.35)
		Candidate	-0.000**	(-2.10)	0.001*	(1.72)	-0.185***	(-19.49)	-0.001***	(-3.72)	-0.002***	(-10.98)
		Adj R^2 (%)	0.195		2.689		0.08		12.671		0.139	
4	Decompose	Candidate	0.015		0.033		-0.053		-0.009		-0.136	
	Stage 1 coef.		-1.19%	(-0.98)	-2.62%*	(-1.84)	4.64%	(0.20)	0.70%	(0.49)	9.58%*	(1.88)
		Residual	-1.285		-0.312		-1.084		-1.226		-1.279	
			101.19%***	(10.28)	102.62%***	(11.74)	95.36%***	(3.70)	99.30%***	(8.67)	90.42%***	(9.35)
	Avg # /mth		3169		2856		2718		2626		2855	

Table 10 – continued

Panel D: Multivariate analysis						
Stage	Description	Variable	Coef.	t-stat	Frac. Expl.	Group
1	Adj. ret. on Eff	Intercept	1.804***	(5.48)		
		Eff	-2.241***	(-4.96)		
2	Adj. ret. on Eff	Intercept	2.600***	(4.15)		
	and candidate	Eff	-2.239***	(-3.29)		
		PYRET	-0.512***	(-2.61)		
		PROA	0.014	(1.39)		
		PEFF	0.922***	(2.75)		
		IVOL	-0.091*	(-1.89)		
		BASK	0.205***	(2.63)		
		AMI	4.243***	(4.05)		
		DVOL	-0.000	(-1.01)		
		FRISC	-0.003	(-0.87)		
		OC	0.119*	(1.81)		
		DD	1.157***	(2.83)		
		O	-0.009	(-0.45)		
		Z	-0.006	(-0.54)		
3	Eff on candidate	Intercept	0.741***	(381.47)		
		PYRET	0.027***	(8.56)		
		P∆ROA	0.000***	(2.86)		
		P∆EFF	0.171***	(19.87)		
		IVOL	-0.003***	(-7.62)		
		BASK	0.005***	(9.36)		
		AMI	-0.192***	(-5.47)		
		DVOL	0.000***	(4.72)		
		FRISC	-0.000***	(-4.46)		
		OC	-0.004***	(-6.57)		
		DD	-0.161***	(-13.55)		
		O	0.009***	(16.08)		
		Z	-0.006***	(-8.80)		
		Adj R^2 (%)	40.408			
4	Decompose	PYRET	-0.372	(3.40)	16.58%***	Past
	Stage 1 coef.	P∆ROA	-0.053	(2.26)	2.36%**	performance
		P∆EFF	-0.015	(0.13)	0.66%	19.60%
		IVOL	-0.428	(6.51)	19.09%***	Limits.
		BASK	-0.310	(0.32)	13.82%***	
		AMI	-0.035	(2.75)	1.56%	
		DVOL	0.190	(-1.56)	-8.45%	26.02%
		FRISC	-0.009	(0.21)	0.41%	Adj. cost
		OC	0.045	(-0.96)	-1.99%	-1.58%
		DD	0.008	(-0.02)	-0.34%	Distress
		O	0.190	(-0.96)	-8.49%	
		Z	-0.329	(2.60)	14.66%***	5.83%
		Residual	-1.123	(5.88)	50.13%***	
	Avg # /mth		1694			

Appendix A. Definition of terms and variables

This table defines the variables used in this study.

AG: Asset growth, calculated as the change in the book value of total assets (item AT) over fiscal year *t* scaled by beginning total assets. Data source: Compustat.

AGE: Firm age, measured as the number of years a stock has appeared in CRSP at the end of June of calendar year *t*+1. Data source: CRSP.

AMI: Amihud (2002) illiquidity, measured as the time-series average of the absolute value of daily returns scaled by the trading day's dollar trading volume over the year ending in June of calendar year *t*+1. Data source: CRSP.

BASK: Bid-ask spread, measured as the time-series average of 2 x |Price–(Ask-Bid)/2|/Price at the end of each month over the 12 months ending in June of year t, where Price is the closing stock price and Ask (Bid) is the ask (bid) quote. Data source: CRSP.

BM: Book-to-market equity ratio, calculated as the book value of equity divided by market capitalization at the end of fiscal year *t*. Book equity is total assets minus liabilities (item LT), plus balance sheet deferred taxes (item TXDB) and investment tax credits (item ITCI), minus preferred stock liquidation value (item PSTKL) if available, or redemption value (item PSTKRV) if available, or carrying value (item PSTK) if available. Data source: Compustat and CRSP.

DD: Distant-to-default based on Merton's (1974) model, as constructed in Vassalou and Xing (2004). Data source: Compustat and CRSP.

DVOL: Average daily dollar trading volume, which is the closing price multiplied by the trading day's share trading volume, over the year ending in June of calendar year *t*+1. Data source: CRSP.

Eff: Efficiency score, estimated using equation 2. Data source: Compustat and CRSP.

FRISC: A composite score for investment frictions, generated from the average percentile rank of firm age, total assets, and payout ratio. Data source: Compustat.

GPA: Gross profitability, calculated as the gross profit (item GP) over a fiscal year *t* scaled by beginning total assets. Data source: Compustat.

GS: Growth in sales, calculated as the average of the annual growth in revenue (item REVT) over the past five fiscal years *t*, *t*–1, *t*–2, *t*–3, *t*–4, and *t*–5. Data source: Compustat.

IK: Investment-to-capital ratio, calculated as capital expenditures (Compustat item CAPX) for fiscal year *t* scaled by the beginning net book value of property, plant, and equipment (item PPENT). Data source: Compustat.

IVOL: Idiosyncratic stock return volatility, estimated as the standard deviation of the residuals from a regression of daily stock returns in month t-1 on the Fama and French (1993) three factors. Data source: CRSP.

LABOR: Employee growth, calculated as the change in the number of employees (item EMP) over fiscal year *t* scaled by beginning number of employees. Data source: Compustat.

LEV: Leverage, measured as the ratio of long-term debt (item DLTT) to the sum of long-term debt and market value of equity at the end of fiscal year *t*. Data source: Compustat and CRSP.

MOM: Past 6-month returns from December calendar year *t*-1 to May of calendar year *t*. Data source: CRSP.

O: Bankruptcy risk score suggested by Ohlson (1980), which is calculated as –4.07×Ln(A) + 6.03×(L/A) – 1.43×(CA – CL)/A + 0.0757×CL/CA – 2.37×NI/A +

0.285×Loss – 1.72×NegBook – 0.521×ΔNI – 1.83×Op/L, where Ln(A) is the natural logarithm of total assets, L is total liabilities (item LT), CA is current assets (item ACT), and CL is current liabilities (item LCT) at the end of a fiscal year t. NI is net income (item NI) for the lagged fiscal year. Loss is equal to one if net income is negative for both a fiscal year and the lagged fiscal year and zero otherwise. NegBook is equal to one if L is greater than A and zero otherwise. ΔNI is the change in net income between a fiscal year and the lagged fiscal year scaled by the sum of the absolute values of the net income for the two years. Op, funds from operations, is income before extraordinary items (item IB) plus income statement deferred tax (item TXDI), if available, plus equity's share of depreciation expenses for a fiscal year, which is depreciation expenses (item DP) multiplied by market capitalization and divided by total assets minus book value of equity plus market capitalization at the end of a fiscal year. Data source: Compustat.

OC: Operating cost is the sum of cost of goods sold and selling, general and administrative expense scaled by total assets. Data source: Compustat.

PΔEff: Change in firm-productivity score, calculated as the three-year average change in productivity score percentile. Data source: CRSP and Compustat.

PΔROA: Change in ROA, calculated as the equally-weighted three-year average change in operating performance. Data source: Compustat.

PRET: Previous-month return. Data source: CRSP.

PYRET: Three-year average annual buy-and-hold return. Data source: CRSP.

ROA: Return on assets or earnings profitability, calculated as operating income before extraordinary items (item IB) over a fiscal year *t* scaled by beginning total assets. Data source: Compustat.

Size: Market value of equity, computed as the closing stock price multiplied by the number of shares outstanding at the end of June of year *t*. Data source: CRSP

TFP: Total factor productivity, sourced from İmrohoroğlu and Tüzel (2014).

Z: Bankruptcy risk score as suggested by Altman's (1968) Z-score. It is computed as: $-1.2\times(CA - CL)/A - 1.4\times\mathrm{RE/A} - 3.3\times\mathrm{EBIT/TA} - 0.60\times\mathrm{MV/L} - 0.999 \times \mathrm{S/TA}$, where RE is retained earnings. EBIT is earnings before interest and taxes. MV is market value of equity as of the end of financial year. S is sales revenue. Data source: Compustat.

β: Capital asset pricing model (CAPM) beta, estimated as the slope coefficient of the time-series regression of monthly stock returns in excess of the risk-free rate on the market return minus the risk-free rate with a full history of 36 months of observations ending in June of calendar year *t*+1. Data source: CRSP and Kenneth French's Data Library.