Journal of Empirical Finance 58 (2020) 139–163

Contents lists available at ScienceDirect

Journal of Empirical Finance

journal homepage: www.elsevier.com/locate/jempfin

Mispricing firm-level productivity

Tze Chuan 'Chewie' Ang [a,*], F.Y. Eric C. Lam [b], K.C. John Wei [c]

[a] Department of Finance, Deakin Business School, Deakin University, Australia
[b] Hong Kong Institute for Monetary and Financial Research, Hong Kong Academy of Finance, Hong Kong Monetary Authority, Hong Kong
[c] School of Accounting and Finance, Faculty of Business, Hong Kong Polytechnic University, Hong Kong

ARTICLE INFO

JEL classification:
D23
D24
G12
G14

Keywords:
Firm-level productivity
Mispricing
Investor sentiment
Extrapolation
Limits to arbitrage

ABSTRACT

This paper provides a mispricing-based explanation for the negative relation between firm-level productivity and stock returns. Investors appear to underprice unproductive firms and overprice productive firms. We find evidence consistent with the speculative overpricing of productive firms driven by investor sentiment and short sale constraints. Investors erroneously extrapolate past productivity growth and its associated operating performance and stock returns, despite their subsequent reversals. Such mispricing is perpetuated because of limits to arbitrage and is partially corrected around earnings announcements when investors are surprised by unexpected earnings news. Decomposition analysis indicates that extrapolative mispricing and limits to arbitrage explain most of the return predictability of firm-level productivity.

1. Introduction

Firm-level productivity refers to a firm's efficiency in converting inputs into outputs. It is a key element in neo-classical investment-based asset pricing models (e.g., Cochrane, 1991, 1996; Liu et al., 2009) that relates the cross-section of stock returns to firm characteristics, such as book-to-market equity (Zhang, 2005) and capital investment (Li et al., 2009).[1] Empirical studies have shown a negative relation between firm productivity and future stock returns. The existing explanations for this "firm productivity effect" are purely based on the risk-return tradeoff: unproductive firms attract a risk premium because they face either a higher distress risk (Nguyen and Swanson, 2009) or steeper adjustment costs in reducing unproductive capital stock (İmrohoroğlu and Tüzel, 2014) compared to productive firms.

Previous studies focus on the risk-based explanations for the firm productivity effect from the firm's perspective. In this paper, we provide an alternative mispricing-based explanation from the investor's perspective. Specifically, we explore the roles of investors' extrapolation of past firm productivity and its associated operating performance and stock returns. Our empirical study serves as a firm-level cross-sectional analysis of Hirshleifer et al. (2015). They show that extrapolative errors drive the negative relation between perceived aggregate technological growth and future market returns. Our hypothesis is motivated by De Bondt and Thaler (1985) and Lakonishok et al. (1994) who find that investors' extrapolative expectation errors lead to stock price reversals when the realized outcome is contrary to their expectations.[2] The literature on limits to arbitrage (Shleifer and Vishny, 1997; Pontiff, 2006) suggests that mispricing is not immediately corrected due to arbitrage frictions. We therefore examine the impact of arbitrage frictions on

* Correspondence to: Department of Finance, Faculty of Business and Law, Deakin University, 221, Burwood Highway, Burwood, Victoria 3125, Australia.
E-mail addresses: c.ang@deakin.edu.au (T.C.'C.' Ang), fyericcl@hkbu.edu.hk (F.Y.E.C. Lam), johnwei@ust.hk (K.C.J. Wei).

[1] Other studies include inventory growth (Jones and Tuzel, 2013), labor hiring (Belo et al., 2014), and price momentum (Liu and Zhang, 2014).

[2] Both surveys and experimental studies have shown that investors' forecasts reflect a trend-following mechanism (De Bondt, 1993). Barberis et al. (2015) show that an asset-pricing model with extrapolative investors is consistent with empirical patterns in stock returns and investors' expectations revealed from surveys. Moreover, retail investors tend to chase recent mutual fund performance (Sirri and Tufano, 1998) and hold overvalued stocks (Frazzini and Lamont, 2008). These fund managers tend to direct capital inflows to their existing stock holdings, exacerbating the extrapolative overvaluation (Lou, 2012).

https://doi.org/10.1016/j.jempfin.2020.05.008
Received 23 December 2019; Received in revised form 27 May 2020; Accepted 30 May 2020
Available online 4 June 2020
0927-5398/

the firm productivity effect. We also highlight the role of speculative overpricing in accentuating the firm productivity effect. More importantly, our analysis quantifies the fraction of return predictability based on firm-level productivity that is attributed to the variables related to mispricing.

We use two measures of firm productivity: a firm's shortfall from its potential optimal value frontier (*PROD*) (Nguyen and Swanson, 2009); and its total factor productivity (*TFP*) (İmrohoroğlu and Tüzel, 2014). Using U.S. data from July 1973 to June 2015, a long-short strategy that buys stocks in the bottom *PROD* decile portfolio and shorts stocks in the top *PROD* decile portfolio earns an average return of more than 1.20% per month. The negative relation between firm productivity and future stock returns is robust over time and even after controlling for various return predictors and factors not included in earlier studies.

We then show that unproductive firms are beaten-down firms with low past stock returns and profits and with a high distress risk and arbitrage costs. In contrast, productive firms are healthy, profitable firms with high past stock returns and good future growth potential. These firms with extreme levels of productivity may be prone to mispricing because of their extreme characteristics and the hard-to-value nature of firm productivity. Using a proxy for relative mispricing, following Stambaugh et al. (2015), we show that investors underprice unproductive firms, but overprice productive firms, and such mispricing is reflected in the return spread.

Investor sentiment exerts a larger impact on stocks that are difficult to value and arbitrage during periods with high sentiment (Baker and Wurgler, 2006), when speculative trading is more common. Moreover, overpricing is more prevalent than underpricing in the presence of short sale impediments, as a firm's stock price reflects the view of optimistic investors (Miller, 1977). Following Stambaugh et al. (2012, 2015), we combine these two ideas and explore the effect of speculative overpricing on the firm productivity effect. We use Baker and Wurgler's (2006) sentiment index as a proxy for market-wide investor sentiment. We find that the return on the long-short strategy based on *PROD* is 60% higher following months with high investor sentiment than following months with low investor sentiment. Furthermore, the short leg of the strategy is more profitable when sentiment is high. In contrast, the underpricing of stocks in the long leg is unaffected by investor sentiment. The evidence suggests that the overpricing of productive firms due to investor sentiment is at least a partial explanation for the firm productivity effect.

We next examine whether investors' extrapolation of past firm productivity and its associated operating performance and stock returns contributes to the mispricing of firm productivity. The results indicate that productive (unproductive) firms experience improvements (deteriorations) in productivity and operating performance *before* portfolio formation, but much of these changes reverse afterward. More importantly, these productivity and performance reversals coincide with stock return reversals. We find that investors are surprised by positive earnings news for unproductive firms and negative earnings news for productive firms. The correction of their valuation errors about firm productivity partially occurs within the three-day window around quarterly earnings announcements, when the information release is contrary to their expectations. Approximately 23% of the annual return of the long-short portfolio strategy occurs within that period.[3]

Arbitrage trading can be risky due to noise traders' erratic activities (De Long et al., 1990), arbitrage capital constraints and career concerns (Shleifer and Vishny, 1997), and transaction costs (Pontiff, 2006). Motivated by this line of reasoning, we examine the role of arbitrage costs in perpetuating the firm productivity effect. Using several proxies for limits to arbitrage, we show that the firm productivity effect is more pronounced among firms with barriers to arbitrage and is weak otherwise. However, the high returns on unproductive firms relative to their productive counterparts may reflect the steeper adjustment costs in reducing unproductive capital stocks during economic downturns (İmrohoroğlu and Tüzel, 2014). Hence, we also examine the role of adjustment costs, given their close empirical relation to limits to arbitrage. We find that investment frictions accentuate the firm productivity effect, but there is no support for the role of operating costs. The role of economic downturns in driving the firm productivity effect is also limited.

Finally, we use the Hou and Loh (2016) decomposition framework to estimate the fractions of the return predictability of *PROD* that are attributed to variables related to the extrapolation of past operating performance, productivity, and stock returns, limits to arbitrage and adjustment costs in a unified framework. This method allows us to directly evaluate the power of the variables in explaining the ability of *PROD* to predict future returns beyond the patterns established in standard portfolio sorts and cross-sectional regressions. As a group, variables related to past productivity growth and past stock returns explain approximately 30% of the return predictability of *PROD* and variables related to limits to arbitrage explain another 45%, leaving approximately 25% of the return predictability unexplained. In contrast, the explanatory power of variables associated with adjustment costs or distress risk is modest. Overall, the decomposition results highlight the importance of extrapolative mispricing with limited arbitrage in driving the firm productivity effect.

We contribute to the literature in several ways. First, we provide firm-level empirical support that the productivity effect can be explained by the extrapolative capital asset-pricing model of Barberis et al. (2015) and the aggregate neoclassical model with extrapolative bias in the productivity growth of Hirshleifer et al. (2015). Our findings also add to the literature on investors' overreaction to past information.[4] Moreover, we corroborate studies that find investors' delayed reaction to information on hard-to-value characteristics and various forms of firm efficiencies.[5] Furthermore, we highlight the importance of short sale constraints and overpricing in mispricing firm productivity and provide out-of-sample support to previous studies that examine the role of

[3] These return and accounting performance patterns are similar to those associated with the book-to-market effect documented by Lakonishok et al. (1994).

[4] For example investors overreact to past stock returns (De Bondt and Thaler, 1985), past operating performance (Lakonishok et al., 1994), and intangible information (Daniel and Titman, 2006). Recently, Fitzgerald et al. (2019) find that investors tend to focus on (overreact to) eye-catching exploratory innovation and neglect (underreact to) the value of incremental, exploitative innovation.

[5] Previous studies on hard-to-value characteristics include the information in corporate linkages (Cohen and Frazzini, 2008) and complicated firms (Cohen and Lou, 2012). Studies on the asset-pricing implication of various forms of firm-level efficiencies include those related to innovative efficiency (Hirshleifer et al., 2013).

speculative mispricing in asset pricing (see Stambaugh et al., 2012 on anomalies; Shen et al., 2017 on macroeconomic factors). Our study also sheds light on the literature on the role of limits to arbitrage in perpetuating return predictability.[6]

2. Data and measures of firm productivity

2.1. Sample

The sample consists of all common stocks (share codes 10 and 11) listed on the NYSE, AMEX, and Nasdaq from 1972 through 2015 inclusive. Stock market data are sourced from the Center for Research in Security Prices (CRSP). Financial data and earnings announcement dates are obtained from Compustat. A stock must have available data to compute the firm productivity measure to be included in the sample. We match monthly stock returns from July of calendar year $t + 1$ to June of calendar year $t + 2$ with financial statements for fiscal year t and firm attributes observed at the end of June of calendar year $t + 1$. All trading strategies are updated at the end of June each year.[7]

2.2. Measuring firm productivity

Firm productivity refers to a firm's efficiency in transforming its inputs into outputs. Following the literature, we use two measures of firm productivity. First, we estimate firm productivity using stochastic frontier analysis (SFA), pioneered by Aigner et al. (1977).[8] Consider a set of firms with different characteristics. Those that can generate the highest value per dollar of assets from the opportunity set they face are deemed efficient (i.e., productive) and they span the optimal efficiency frontier. Other firms that are not on the frontier are relatively inefficient and how much they fall short from the frontier forms investors' perception of lack of productivity.

To empirically identify the unobservable frontier, we use the firm characteristics used by Habib and Ljungqvist (2005) and Nguyen and Swanson (2009). SFA allows us to distinguish between random noise and shortfall from the empirical frontier due to structural firm inefficiency.[9] At the end of June every calendar year *t*, we estimate the following cross-sectional regression:

$$\begin{aligned}\ln(ME)_i &= \alpha + \beta_1 \ln(BE)_i + \beta_2 \ln\left(\frac{D}{A}\right)_i + \beta_3\left(\frac{CAPX}{SALES}\right)_i + \beta_4\left(\frac{RD}{SALES}\right)_i + \beta_5\left(\frac{AD}{SALES}\right)_i \\ &\quad + \beta_6\left(\frac{PPE}{TA}\right)_i + \beta_7\left(\frac{EBITDA}{TA}\right)_i + \gamma_j + v_i + \mu_i, \end{aligned} \tag{1}$$

where ln(*ME*) is the natural logarithm of market equity, ln(*BE*) is the natural logarithm of book equity, *D/A* is the ratio of long-term debt to total assets, and *CAPEX/SALES*, *RD/SALES*, and *AD/SALES* are capital expenditures, research and development expenses, and advertising expenses, respectively, scaled by sales. *PPE/TA* and *EBITDA/TA* are property, plant, and equipment and operating profits, respectively, scaled by total assets. We include Fama and French's (1997) 49 industry dummies, γ_j to control for inter-industry differences in firm productivity. v_i (normally distributed) is the two-sided random white noise that accounts for measurement errors and shocks beyond a firm's control (e.g., luck). μ_i (exponentially distributed) captures a firm's inefficiency (i.e., its structural shortfall from the optimal efficiency frontier). The covariance between v and μ is assumed to be zero.

After estimating the parameters and identifying the optimal frontier, a firm's annual productivity score ($PROD_i$) is computed as follows:

$$PROD_i = \frac{E\left(V_i|\mu_i, X_i\right)}{E\left(V_i^*|\mu_i = 0, X_i\right)}, \tag{2}$$

where X is the set of firm characteristics and industry variables, $E\left(V_i\right)$ is the predicted value from Eq. (1), and $E\left(V_i^*\right)$ is the empirical frontier with zero inefficiency (i.e., $\mu_i = 0$). $PROD_i$ is normalized and ranges between 0.00 and 1.00.[10] To alleviate the concern that our measure of firm-level productivity is model specific, we also follow İmrohoroğlu and Tüzel (2014) to use firm-level total factor productivity (*TFP*) (sourced from Selale Tüzel). The online Supplementary Appendix provides a brief description of the estimation procedure and the results.

[6] References include Ali et al. (2003) (value effect), McLean (2010) (momentum and reversal), Lam and John Wei (2011) and Lipson et al. (2011) (investments and asset growth), and others.

[7] We exclude financial (SIC codes 6000 to 6999) and regulated utility (SIC codes 4900 to 4999) firms and stocks priced below $1 per share as of the end of June every year. To mitigate the backfill bias, we exclude firms that appear on Compustat for less than two years. The financial data are from fiscal year 1972 to fiscal year 2014. The monthly holding period returns are from the end of July 1973 to the end of June 2015. We use monthly delisting returns from the CRSP tapes if they are available to mitigate the survivorship bias. Following Shumway (1997), we replace missing delisting returns with −0.30 for stocks delisted from NYSE or AMEX and −0.55 for stocks delisted from Nasdaq.

[8] This estimation technique is commonly used in the finance literature (e.g., Habib and Ljungqvist, 2005; Nguyen and Swanson, 2009).

[9] Because the ordinary least squares (OLS) estimation method cannot make this differentiation, SFA is needed.

[10] A score of 1.00 (0.90) implies that the firm is the most productive (90% of its most-productive peer).

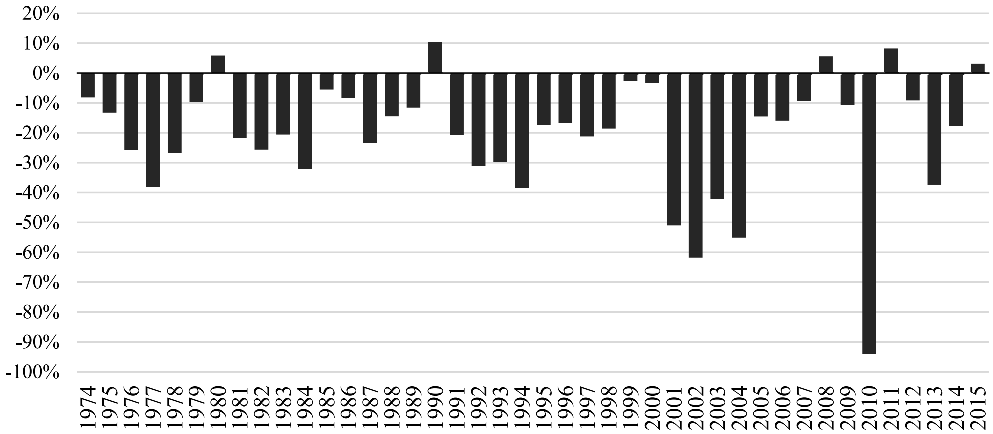

Fig. 1. Annual returns to the long-short portfolio based on firm productivity score. At the end of June every year, we sort firms into 10 portfolios based on firm productivity score. Decile 1 contains firms with the lowest productivity score (unproductive firms). Decile 10 contains firms with the highest productivity score (productive firms). This figure plots the annual buy-and-hold returns to equal-weighted portfolio of longing productive firms and shorting unproductive firms.

3. Firm productivity, stock returns, and characteristics

3.1. Fama-MacBeth regressions

Panel A of Table 1 presents the results of monthly Fama and MacBeth (1973) regressions to compare the return predictability of *PROD* versus *TFP* and other control variables documented in previous studies.[11] The univariate tests in Models 1 and 2 indicate that *PROD* (coeff = −4.886; t-stat = −6.17) and *TFP* (coeff = −0.393; t-stat = −2.76) are significantly and negatively related to future stock returns. When we include both measures in Model 3, the *PROD* coefficient remains significant (t-stat = −5.28), while the *TFP* coefficient is still negative but no longer significant (t-stat = −1.58).

In Models 4 to 8, we include the logarithm of market equity (ln(*ME*)), the logarithm of book-to-market ratio (ln(B/M)), past six-month stock return (*P6MRET*), and past one-month stock return (*P1MRET*) as control variables. When we include *PROD* in Model 5, its coefficient remains significant (coeff = −3.894; t-stat = −3.52) and it absorbs the predictive power of ln(B/M). The negative *PROD* coefficient remains significant in Models 6 to 8 when we control for total assets growth (*TAG*), gross profitability (*GP/A*), and financial leverage (*LEV*), respectively.[12]

3.2. Portfolio returns and factor loadings

Panel B of Table 1 presents the equal-weighted average returns on decile portfolios sorted by *PROD*. In general, portfolio returns decrease monotonically as firm productivity increases. The differences in average raw returns (*RET*) between productive and unproductive firms (10-1) is −1.20% (t-stat = −6.90). The corresponding alpha based on the Fama and French (2015) five-factor model augmented with the Carhart (1997) momentum factor (FF6) is −1.11% (t-stat = −8.59) and the alpha for the Hou et al. (2015) q-factor model (HXZ) is −1.25% (t-stat = −7.54).[13] These risk adjustments do not change the magnitude of the return spread by much. Moreover, the annualized return spread is also persistent throughout our sample period (as shown in Fig. 1). All these results are not easy to be reconciled with the risk-based explanations.

Panel C of Table 1 presents the factor loadings on *PROD* portfolios. Both productive and unproductive firms load positively on the market and size factors. However, productive firms are more exposed to the market factor, but less to the size factor than unproductive firms. Productive firms load negatively, while unproductive firms load positively on the value factor. Although both productive and unproductive firms load negatively on the momentum factor, the exposure of the latter is higher. Both productive and unproductive firms load negatively on the investment and profitability factors. Their exposures are not significantly different. Overall, productive firms behave like large growth stocks with high past returns, relative to unproductive firms.

[11] We do not include industry dummies because *PROD* is estimated with industry fixed effects. See Eqs. (1) & (2).

[12] Unreported results show that the negative coefficient on *PROD* remains significant when we control for other proxies for growth, such as inventory growth, sales growth, and investment growth, and other measures of profitability, such as net income scaled by total assets. We also find that the input variables used to generate *PROD* do not explain future returns. As the return patterns with *PROD* are similar to those with *TFP* and *PROD* subsumes *TFP* in predicting returns, we only report the results with *PROD*, leaving those with *TFP* in the Online Appendix A.

[13] Table A.1 in the Online Appendix shows that the return spreads are significantly negative relative to other factor models.

Table 1

Firm productivity and stock returns: Fama–MacBeth regressions, portfolio returns and factor loadings.

Panel A reports slopes from monthly Fama and MacBeth (1973) regressions of future stock returns on firm characteristics. *PROD* is firm productivity score, *TFP* is firm-level total factor productivity, *TAG* is total asset growth, *GP/A* is gross profitability, *LEV* is financial leverage, ln(*ME*) is the log of market equity, ln(*B/M*) is the log of the book-to-market ratio, *P6MRET* is past six-month return, and *P1MRET* is past one-month return. Panel B reports the average monthly returns and alphas (%) from factor models. *RET* refers to the time-series average of monthly portfolio returns. The alphas are returns after benchmarking to the Fama and French (2015) five factors augmented with the Carhart (1997) momentum factor (FF6) or the Hou et al. (2015) q factors (HXZ). Panel C reports the FF6 factor loadings. β_{MKT}, β_{SMB}, β_{HML}, β_{RMW}, β_{CMA}, and β_{WML} are loadings corresponding to the market, size, value, profitability, investment, and momentum factors. At the end of June every year, we sort stocks into 10 portfolios based on *PROD*. Decile 1 has the lowest productivity, while decile 10 has the highest productivity. The equal-weighted portfolios are rebalanced every year. Portfolio returns are from July of the sorting year through June of the following year. The sample period is from July 1973 through June 2015. (10-1) is the difference between *PROD* deciles 10 and 1. The *t*-statistics in parentheses are corrected for autocorrelation using the Newey and West (1987) standard errors with 12 lags. ***, ** and * denote significance at the 1%, 5% and 10% levels.

Panel A: Fama–MacBeth regressions

	Model							
	1	2	3	4	5	6	7	8
Intercept	4.994***	1.355***	5.079***	1.724***	4.388***	4.661***	4.412***	4.587***
	(7.02)	(5.60)	(6.33)	(4.02)	(4.37)	(4.72)	(4.40)	(4.52)
PROD	−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					
		(−2.76)	(−1.58)					
TAG						−0.361***		
						(−5.60)		
GP/A							0.548***	
							(3.10)	
LEV								−0.477*
								(−1.67)
ln(*ME*)				−0.056	−0.030	−0.028	−0.028	−0.028
				(−1.27)	(−0.71)	(−0.66)	(−0.67)	(−0.65)
ln(*B/M*)				0.304***	0.098	0.024	0.083	0.129
				(3.61)	(0.79)	(0.20)	(0.67)	(1.12)
P6MRET				0.318**	0.475***	0.481***	0.471***	0.484***
				(2.15)	(3.05)	(3.05)	(3.07)	(3.08)
P1MRET				−0.049***	−0.049***	−0.049***	−0.050***	−0.050***
				(−8.18)	(−8.18)	(−8.23)	(−8.26)	(−8.38)

PROD	1 (Low)	2	3	4	5	6	7	8	9	10 (High)	(10 − 1)
Panel B: Portfolio returns											
RET	1.95***	1.67***	1.58***	1.49***	1.43***	1.35***	1.32***	1.11***	1.02***	0.75**	−1.20***
	(5.74)	(5.55)	(5.48)	(5.48)	(5.41)	(5.35)	(5.16)	(4.37)	(3.71)	(2.36)	(−6.90)
FF6	0.90***	0.63***	0.47***	0.34***	0.28***	0.20***	0.16**	0.04	0.02	−0.21*	−1.11***
	(5.60)	(5.03)	(4.13)	(4.20)	(3.13)	(2.80)	(1.98)	(0.42)	(0.18)	(−1.77)	(−8.59)
HXZ	1.08***	0.75***	0.60***	0.45***	0.34***	0.29***	0.22*	0.10	0.06	−0.17	−1.25***
	(5.83)	(4.94)	(4.16)	(3.99)	(2.65)	(3.04)	(1.87)	(0.83)	(0.52)	(−1.06)	(−7.54)
Panel C: Factor loadings											
β_{MKT}	0.90***	0.91***	0.94***	0.99***	0.98***	1.00***	1.03***	1.02***	1.06***	1.09***	0.19***
	(22.41)	(30.69)	(30.81)	(40.97)	(46.45)	(40.74)	(45.77)	(40.91)	(50.17)	(40.35)	(5.29)
β_{SMB}	1.12***	1.07***	1.00***	0.97***	0.91***	0.88***	0.84***	0.76***	0.75***	0.79***	−0.33***
	(16.27)	(27.40)	(19.49)	(26.19)	(22.99)	(22.48)	(19.20)	(14.24)	(14.95)	(13.15)	(−5.15)
β_{HML}	0.20***	0.12***	0.19***	0.12***	0.10**	0.05	0.02	−0.04	−0.14***	−0.30***	−0.50***
	(2.89)	(2.72)	(4.11)	(2.65)	(2.19)	(0.81)	(0.40)	(−0.73)	(−2.64)	(−5.01)	(−7.58)
β_{RMW}	−0.30***	−0.25***	−0.10*	−0.08*	−0.03	0.01	0.06	0.01	−0.09	−0.26***	0.04
	(−3.24)	(−3.82)	(−1.84)	(−1.92)	(−0.67)	(0.21)	(1.12)	(0.16)	(−1.63)	(−4.02)	(0.34)
β_{CMA}	0.03	0.02	−0.03	0.05	0.03	0.05	0.01	−0.08	−0.15*	−0.14	−0.17
	(0.21)	(0.21)	(−0.24)	(0.62)	(0.48)	(0.77)	(0.10)	(−0.99)	(−1.92)	(−1.64)	(−1.35)
β_{WML}	−0.31***	−0.27***	−0.22***	−0.21***	−0.18***	−0.18***	−0.16***	−0.15***	−0.16***	−0.11**	0.20***
	(−5.41)	(−5.01)	(−4.88)	(−5.43)	(−4.85)	(−5.30)	(−4.07)	(−3.55)	(−4.00)	(−2.52)	(5.37)

3.3. Portfolio characteristics before portfolio formation

Table 2 reports the time-series averages of cross-sectional median characteristics of decile portfolios sorted by *PROD*. Productive (Unproductive) firms experience an increase (decrease) in productivity over the previous three years. Productive firms are larger in market equity, but slightly younger than unproductive ones. They also have higher market betas. Moreover, productive (unproductive) firms have positive (negative) stock returns over the past one month, six months, and three years. Productive firms have higher growth in sales, total assets, and investments in capital stock and human resources. They also have a lower book-to-market equity and a higher price to cash flow ratio (i.e., better valuations). Furthermore, they have better performance in terms of gross profitability and return on assets in the sorting year, accompanied by a substantial improvement in performance over the previous three years.

Table 2
Characteristics of firm productivity portfolios.
This table reports the time-series averages of annual median characteristics of portfolios sorted by firm productivity score (*PROD*). The characteristics include firm productivity score (*PROD*), average year-to-year change in *PROD* over the previous three years (*3Y ΔPROD*), market equity (*ME*), firm age (*AGE*), CAPM beta (*β*eta), past one-month return (*P1MRET*), past six-month return (*P6MRET*), past three-year return (*P3YRET*), growth in sales (*GS*), total asset growth (*TAG*), investment-to-capital ratio (*I/K*), labor hiring (*HIRING*), the book-to-market ratio (*B/M*), price-to-cash flow ratio (*P/CF*), gross profitability (*GP/A*), return on assets (*ROA*), average year-to-year change in *ROA* over the past three years (*3Y ΔROA*), financial leverage (*LEV*), the Merton (1974) distance-to-default (*DD*), the Ohlson (1980) O-score (*O-score*), the Altman (1968) Z-score (*Z-score*), investment frictions (*IF*), operating cost (*OC*), idiosyncratic stock return volatility (*IVOL*), the Amihud (2002) price impact (*ILLIQ*), effective bid–ask spread (*BIDASK*) and dollar trading volume (*DVOL*). All variables are defined in the Appendix. At the end of June every year, we sort stocks into 10 portfolios based on *PROD*. Decile 1 has the lowest productivity, while decile 10 has the highest productivity. The portfolios are rebalanced every year. The sample period is from 1973 through 2015. (10-1) is the difference between *PROD* deciles 10 and 1. The *t*-statistics (*t*-stat) in parentheses are corrected for autocorrelation using the Newey and West (1987) standard errors with one lag. ***, ** and * denote significance at the 1%, 5% and 10% levels.

PROD	1 (Low)	2	3	4	5	6	7	8	9	10 (High)	(10 − 1)	*t*-stat
General characteristics												
PROD	0.63	0.68	0.71	0.73	0.75	0.76	0.77	0.79	0.80	0.83	0.21***	(79.79)
3Y ΔPROD	−0.04	−0.05	−0.04	−0.03	−0.01	0.00	0.01	0.02	0.02	0.02	0.06***	(18.08)
ME (millions)	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 (years)	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*eta	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 stock returns (%)												
P1MRET	−2.53	−1.50	−0.97	−0.48	−0.31	0.25	0.65	1.15	1.57	2.06	4.59***	(8.01)
P6MRET	−3.87	1.21	4.15	6.81	8.98	11.06	12.56	14.46	16.94	21.25	25.13***	(12.47)
P3YRET	−5.68	1.26	5.38	9.43	12.56	15.55	18.19	22.09	27.71	33.89	39.57***	(14.16)
Growth												
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)
TAG	0.01	0.03	0.05	0.07	0.08	0.09	0.10	0.12	0.14	0.16	0.15***	(13.94)
I/K	0.19	0.21	0.21	0.22	0.22	0.23	0.24	0.25	0.28	0.32	0.13***	(16.22)
HIRING	−0.01	0.01	0.01	0.02	0.03	0.04	0.05	0.06	0.07	0.10	0.11***	(18.72)
B/M	1.79	1.28	1.06	0.93	0.80	0.70	0.60	0.50	0.37	0.20	−1.59***	(−19.43)
P/CF	6.12	6.64	6.96	7.19	7.64	8.17	8.91	10.13	12.90	22.67	16.55***	(6.48)
Profitability												
GP/A	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)
3Y ΔROA	−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)
O-score	−0.75	−1.09	−1.33	−1.43	−1.56	−1.66	−1.69	−1.76	−1.68	−1.32	−0.58***	(−4.30)
Z-score	−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 costs												
IF	50.07	48.95	47.65	46.36	45.05	44.10	44.17	44.78	47.41	54.30	4.22***	(6.07)
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)
Arbitrage 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)
ILLIQ	2.22	1.95	1.47	1.19	0.88	0.66	0.52	0.38	0.24	0.21	−2.01***	(−6.36)
BIDASK	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)

Despite using different inputs and estimation methods to measure firm productivity, we find the characteristics of portfolios sorted by *PROD* to be similar to those sorted by *TFP* (see Table 1 of İmrohoroğlu and Tüzel, 2014). We extend their analysis by showing that productive firms have lower financial leverage and face lower distress risk. Although productive firms have higher investment frictions, both productive and unproductive firms face similar operating costs. Furthermore, productive firms are subject to lower arbitrage costs, in terms of lower idiosyncratic stock return volatility, lower Amihud's (2002) illiquidity (a proxy for price impact), lower effective bid–ask spreads, and higher dollar trading volume.

4. Testing the mispricing explanation for the firm productivity effect

4.1. The role of mispricing and market-level investor sentiment

Previous studies have suggested that investors misprice the stocks of firms with hard-to-value characteristics, such as intangible information (Daniel and Titman, 2006), information in complicated firms (Cohen and Lou, 2012), and innovative efficiency (Cohen et al., 2013; Hirshleifer et al., 2013). Unlike salient characteristics, such as profitability and firm size, firm-level productivity is difficult to observe and may be prone to mispricing, especially by unsophisticated investors.

Table 3

Mispricing, investor sentiment, and the firm productivity effect.

For Panels A, C, and D, we sort stocks into 10 portfolios based on the firm productivity score (*PROD*) at the end of June every year. The equal-weighted portfolios are rebalanced every year. Panel A reports the time-series average mispricing score (*MISP*) of the deciles. To compute *MISP*, we independently sort stocks into 11 percentiles based on 11 firm characteristics known to predict abnormal returns in the equity anomalies literature: bankruptcy probabilities, net stock issuance, composite equity issuance, total accruals, net operating assets, past 12-month return, gross profitability, total asset growth, return on assets, and investment-to-assets. A ranking is in ascending (descending) order if the anomaly variable negatively (positively) predicts returns. A firm's *MISP* is the arithmetic average of the 11 ranked values it receives in a given year. Firms with high (low) *MISP* generate low (high) abnormal returns and are relatively overpriced (underpriced). Panel B reports the average monthly returns (%) on equal-weighted portfolios independently sorted by quintiles of *PROD* and quintiles of *MISP*. It also shows the returns on trading strategy that longs underpriced unproductive firms (L1) and shorts overpriced productive firms (S1) versus trading strategy that longs overpriced unproductive firms (L2) and shorts underpriced unproductive firms (S2). Panel C reports the average returns on the *PROD* deciles across low and high investor sentiment periods. A month is of high (low) sentiment when the Baker and Wurgler (2006) sentiment index in the previous month is above (below) the sample median. Panel D presents the sensitivities of returns to the Baker and Wurgler (2006) sentiment index from regressing portfolio excess returns on the Fama and French (2015) five factors, momentum factor, and previous month sentiment index. Panel E reports the average returns of the trading strategy that longs underpriced unproductive firms (L1) and shorts overpriced productive firms (S1) across low and high investor sentiment periods. The sample period is from July 1973 through June 2015. The *t*-statistics (*t*-stat) in parentheses are corrected for autocorrelation using the Newey and West (1987) standard errors with 12 lags. ***, ** and * denote significance at the 1%, 5% and 10% levels.

Panel A: Average mispricing score

PROD	1 (Low)	2	3	4	5	6	7	8	9	10 (High)	(10 – 1)	*t*-stat
MISP	48.82	48.3	48.18	48.11	47.84	47.86	47.85	47.64	48.6	50.36	1.54**	(2.92)

Panel B: Returns (%) of portfolios sorted by firm productivity score and mispricing score

	MISP					
PROD	1 (Underpriced)	2	3	4	5 (Overpriced)	(5 – 1)
1 (Low)	2.10	2.06	1.90	1.77	1.20	-0.90***
	(7.25)	(6.89)	(5.65)	(5.39)	(3.21)	(-4.84)
2	1.82	1.68	1.72	1.42	0.96	-0.86***
	(7.34)	(6.46)	(6.00)	(4.87)	(2.74)	(-4.89)
3	1.69	1.51	1.52	1.34	0.78	-0.91***
	(7.19)	(6.42)	(5.75)	(5.09)	(2.37)	(-5.47)
4	1.45	1.37	1.31	1.18	0.73	-0.72***
	(6.50)	(5.73)	(5.34)	(4.23)	(2.29)	(-4.58)
5 (High)	1.31	1.16	1.07	0.78	0.28	-1.03***
	(4.64)	(4.50)	(3.57)	(2.70)	(0.74)	(-5.55)
(5 – 1)	-0.79***	-0.90***	-0.84***	-0.99***	-0.93***	-0.13
	(-4.85)	(-5.76)	(-4.58)	(-6.32)	(-5.19)	(-0.80)

Trading strategies	L1	S1	(L1 – S1)	L2	S2	(L2 – S2)
	2.10***	0.28	1.82***	1.20***	1.31***	-0.11
	(7.25)	(0.74)	(7.84)	(3.21)	(4.64)	(-0.50)

PROD	1 (Low)	2	3	4	5	6	7	8	9	10 (High)	(1 – 10)
Panel C: Investor sentiment and the firm productivity effect											
High sentiment											
	1.54***	1.33***	1.24***	1.23***	1.11***	1.08***	0.95***	0.72*	0.54	0.07	1.47***
	(3.92)	(3.52)	(3.39)	(3.42)	(3.15)	(3.00)	(2.68)	(1.93)	(1.35)	(0.15)	(6.57)
Low sentiment											
	2.35***	2.01***	1.93***	1.74***	1.75***	1.62***	1.69***	1.50***	1.50***	1.44***	0.92***
	(4.84)	(4.44)	(4.51)	(4.06)	(4.25)	(3.99)	(4.15)	(3.82)	(3.65)	(3.27)	(4.29)
High-minus-Low sentiment											
	-0.81	-0.68	-0.69	-0.51	-0.64	-0.54	-0.74*	-0.75*	-0.96**	-1.37***	0.56**
	(-1.59)	(-1.44)	(-1.54)	(-1.20)	(-1.52)	(-1.32)	(-1.73)	(-1.82)	(-2.06)	(-2.62)	(2.04)
Panel D: Sensitivity to lagged investor sentiment											
	-0.08	-0.05	-0.17*	-0.05	-0.09	-0.05	-0.16**	-0.13*	-0.11	-0.26***	0.18***
	(-0.66)	(-0.52)	(-1.67)	(-0.67)	(-1.23)	(-0.78)	(-2.24)	(-1.65)	(-1.56)	(-3.09)	(2.62)

(*continued on next page*)

To test this possibility, we follow Stambaugh et al. (2015) and construct a proxy for relative mispricing based on asset-pricing anomalies documented in the literature that challenge risk-based explanations. First, we independently sort stocks into 11 percentile portfolios based on 11 firm characteristics documented in the equity anomalies literature to predict returns.[14] The relative mispricing measure (*MISP*) of a firm is the arithmetic average of the 11 rankings it receives in a given year. Following Stambaugh et al. (2015), we interpret that stocks in the portfolio with the highest (lowest) mispricing score are the most (least) overpriced.

[14] They include bankruptcy probabilities, net stock issuance, composite equity issuance, total accruals, net operating assets, past 12-month return, gross profitability, asset growth, return on assets, and investment-to-assets. A ranking is in ascending (descending) order if the anomaly variable negatively (positively) predicts returns.

Table 3 (*continued*).

Panel E: Investment sentiment, mispricing and the firm productivity effect

	L1	S1	(L1 – S1)
High sentiment			
	1.86***	-0.76*	2.62***
	(5.76)	(-1.79)	(10.08)
Low sentiment			
	2.34***	1.31***	1.03***
	(5.23)	(2.63)	(4.93)
High-minus-Low sentiment			
	-0.48	-2.07***	1.59***
	(-0.92)	(2.92)	(4.24)

Panel A of Table 3 presents the mispricing scores of the decile portfolios sorted by *PROD*. Productive firms are relatively overpriced compared to unproductive firms. The difference in *MISP* is significant with a value of 1.54 (t-stat = 2.92). Moreover, productive firms in decile 10 are relatively overpriced compared to firms in other deciles with lower productivity. However, while we show that *PROD* is positively correlated with *MISP*, they may represent distinct mispricing effects. To test this conjecture, we independently sort stocks into 5 × 5 portfolios based on their *MISP* and *PROD* to examine their joint impact on stock returns. Panel B of Table 3 shows that a trading strategy that exploits the mispricing of both *PROD* and *MISP* (i.e., longs underpriced unproductive firms and shorts overpriced productive firms) generates a return of 1.82% per month (t-stat = 7.84). This strategy earns twice as much return as the one that is solely based on *PROD* or *MISP*.[15] In contrast, a trading strategy that longs overpriced unproductive firms and shorts underpriced productive firms makes an insignificant loss of −0.11% per month (t-stat = −0.50). The result supports our conjecture that the firm productivity effect is distinct from the general mispricing effect captured by the *MISP* score.

Recall that Table 2 shows that unproductive firms are beaten-down firms with low past stock returns, growth, and profits, but high distress risk and arbitrage costs, whereas productive firms are healthy, profitable firms with high past stock returns and good growth potential. Moreover, both productive and unproductive firms are prone to valuation errors perhaps due to their complex characteristics. Previous studies have found that speculative demand, particularly when investor sentiment is high, drives the mispricing of stocks that are more sensitive to subjective valuation (e.g., Baker and Wurgler, 2006). Firms with extreme levels of productivity (deciles 1 and 10) are potentially attractive to different types of speculators – both optimistic and pessimistic speculators – with subjective valuations. Moreover, the overpricing of productive firms may be sustained in the presence of short sale constraints and optimistic investors, as the prevailing stock prices reflect the view of optimistic investors (e.g., Miller, 1977).

We explore the role of speculative overpricing in driving the firm productivity effect. A trading strategy with a long position in unproductive firms and a short position in productive firms should be more profitable following periods of high sentiment when the propensity to speculate on these firms' future prospects is high. Combined with Miller's (1977) argument of short sale constraints, we expect productive firms (i.e., the short leg of the strategy, *PROD* decile 10) to be more overpriced and hence deliver a higher trading profit following periods of high sentiment. In contrast, the return on unproductive firms (i.e., the long leg of the strategy, *PROD* decile 1) should remain similar in periods with high or low sentiment. We measure market-wide sentiment with the Baker and Wurgler (2006) investor sentiment index.[16] Following Stambaugh et al. (2012), we classify a month as a high (low) sentiment month if the sentiment index in the previous month is above (below) the sample median. Panel C of Table 3 shows that the return on the long-short strategy is 1.47% (t-stat = 6.57) when investor sentiment is high and 0.92% (t-stat = 4.29) when investor sentiment is low. The magnitude of the high-sentiment return spread is 60% ((1.47–0.92)/0.92) larger than that of the low-sentiment spread by 0.56% per month (t-stat = 2.04). Moreover, the short leg of the trading strategy (i.e., *PROD* decile 10) is 1.37% per month (t-stat = 2.62) more profitable following high sentiment periods than low sentiment periods. However, investor sentiment exhibits much less impact on the returns on the long leg of the strategy (i.e., *PROD* decile 1) given that the return difference between high and low sentiment periods is insignificant (0.81% per month, t-stat = 1.59).

We further regress the excess returns on the portfolios sorted by *PROD* on the level of investor sentiment index in the previous month and the Fama and French (2015) five factors augmented with the Carhart (1997) momentum factor. Panel D of Table 3 reports the sensitivities to the lagged sentiment index. The return on the long-short strategy loads positively with a value of 0.18 (t-stat = 2.62) on past sentiment. The short leg of the strategy (*PROD* decile 10) is significantly negatively related to past sentiment with a sensitivity of −0.26 (t-stat = −3.09), but the long leg of the strategy (*PROD* decile 1) is not significantly related to past sentiment. The regression results further support the results of the portfolio sorts.

Panel E of Table 3 examines the combined impact of mispricing score (*MISP*) and investor sentiment on the return predictability of *PROD*. A long-short strategy that exploits the combined trading strategy of *MISP* and *PROD* (i.e., long underpriced unproductive firms and short overpriced productive firms) earns a profit of 2.62% per month in periods with high investor sentiment. It is 1.59% (t-stat = 4.24) higher than the profit in periods with low investor sentiment. Again, the short leg of the strategy contributes to a larger profit when sentiment is high. The difference in profit is a significant 2.07% (t-stat = 2.92) between periods with high and

[15] For comparison, the quintile returns spread based on *PROD* is −0.92% (t-stat = −6.21) and −0.88% on *MISP*.

[16] The sentiment index is provided by Jeffrey Wurgler. It is based on six proxies: the close-end fund discount, the NYSE share turnover, the number of initial public offerings, the average first-day return of initial public offerings, the equity share in new issue, and the dividend premium.

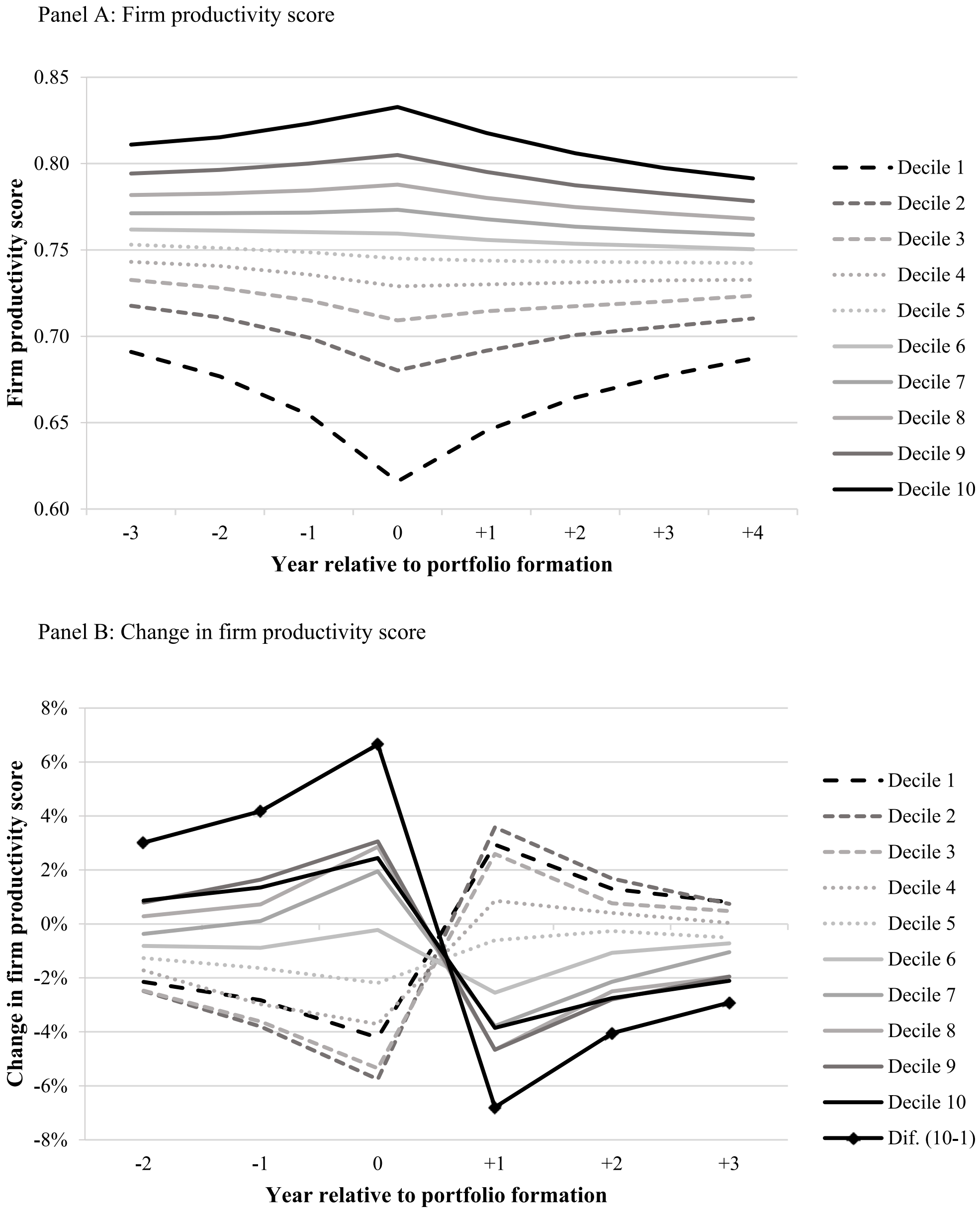

Fig. 2. Firm productivity score and year-to-year change in firm productivity score in event time. At the end of June every year, we sort firms into 10 portfolios based on firm productivity score. Decile 1 contains firms with the lowest productivity score (unproductive firms). Decile 10 contains firms with the highest productivity score (productive firms). Dif. (10-1) is the difference between deciles 10 and 1. Panels A and B plot the time-series averages of the median firm productivity score and year-to-year change in firm productivity score, respectively, for each of the deciles in event time. Year 0 is the sorting year.

low sentiment. In contrast, the profit in the long leg of the strategy is similar between periods with high and low sentiment (diff = −0.48%; t-stat = −0.92).

Taken together, the results suggest that investors underprice unproductive firms and overprice productive firms. The speculative overpricing of productive firms driven by investor sentiment appears to be at least a partial explanation for the mispricing of firm productivity. The evidence of mispricing motivates us to look deeper into the specific forms of investor biases and impediments to arbitrage that perpetuate the mispricing of firm productivity in the following sections.

4.2. The extrapolation of past productivity, performance, and stock returns

Extrapolation bias is an important erroneous belief in investor psychology (e.g., Hirshleifer, 2001; Barberis and Thaler, 2003). Retail or less sophisticated investors are known to be prone to be performance chasers that direct capital to mutual funds that

Table 4
Reversals in productivity growth, operating performance growth, and stock returns.
At the end of June every year, we sort stocks into 10 portfolios based on the firm productivity score (*PROD*). The equal-weighted portfolios are rebalanced every year. Panel A reports the average year-to-year changes in *PROD* of unproductive firms (*PROD* decile 1) and productive firms (*PROD* decile 10) over the three years prior to the sorting year (Pre-sorting) and three years after the sorting year (Post-sorting) together with their differences. Panel B reports the average year-to-year changes in operating performance (*ROA*) over the three years prior to the sorting year and three years after the sorting year. Panel C reports the average annual buy-and-hold returns over the three years prior to the sorting year and three years after the sorting year. The sample period is from July 1973 through June 2015. The t-statistics in parentheses are corrected for autocorrelation using the Newey and West (1987) standard errors with three lags. ***, ** and * denote significance at the 1%, 5% and 10% levels.

	Unproductive	Productive	Productive–Unproductive
Panel A: Change in firm productivity score (%)			
Pre-sorting	−3.06***	1.55***	4.61***
	(−15.92)	(10.39)	(11.13)
Post-sorting	1.68***	−2.90***	−4.58***
	(12.71)	(−11.66)	(−18.80)
Post-sorting–Pre-sorting	4.74***	−4.45***	−9.19***
	(18.71)	(−14.05)	(−13.02)
Panel B: Change in operating performance (%)			
Pre-sorting	−0.85***	0.70***	1.56***
	(−7.62)	(6.27)	(7.93)
Post-sorting	0.35***	−0.58***	−0.93***
	(8.02)	(−6.58)	(−10.09)
Post-sorting–Pre-sorting	1.20***	−1.28***	−2.49***
	(10.33)	(−7.77)	(−9.38)
Panel C: Annual buy-and-hold returns (%)			
Pre-sorting	1.83**	31.38***	29.55***
	(2.20)	(10.18)	(9.80)
Post-sorting	21.18***	7.39***	−13.79***
	(10.07)	(5.05)	(−6.11)
Post-sorting–Pre-sorting	19.35***	−23.99***	−43.34***
	(11.37)	(−6.64)	(−12.66)

have strong recent performance (Sirri and Tufano, 1998) and hold overvalued stocks (Frazzini and Lamont, 2008). Survey results show that investors build their expectations upon recently observed performance (Greenwood and Shleifer, 2014) and that investor forecasts reflect trend-following behavior (De Bondt, 1993).

Using a production-based model with a recursive preference, Hirshleifer et al. (2015) argue that perceived aggregate technological growth negatively predicts aggregate stock returns because investors are subject to extrapolation bias.[17] Empirical evidence also shows that investors overreact to past stock returns (De Bondt and Thaler, 1985), performance growth (Lakonishok et al., 1994), and intangible information (Daniel and Titman, 2006). As shown in Table 2, productive firms have a more glamorous history, such as higher growth in profitability and stock returns, than unproductive firms. More importantly, productive firms receive higher valuations than unproductive ones. Motivated by these findings, we examine the role of expectation errors due to extrapolation in driving the firm productivity effect. A reversal in firm productivity and operating performance with a similar pattern in stock returns before and after portfolio formation is consistent with investors' correction in valuation error.

Panel A of Table 4 reports the change in firm productivity scores (*PROD*) around the sorting year (year 0). During the three-year window *before* the sorting year, the average change in *PROD* (*3YΔPROD*) decreases by 3.06% for unproductive firms, but increases by 1.55% for productive firms. During the three-year window *after* the sorting year, the opposite is true: *3YΔPROD* increases by 1.68% for unproductive firms, but decreases by 2.90% for productive firms. Panel A of Fig. 2 shows that almost all of the initial divergence in *PROD* gradually converges after the sorting year. The positive (negative) productivity shocks to productive (unproductive) firms before the sorting year and the subsequent reversals of these shocks are obvious in Panel B.

Panel B of Table 4 reports the results of operating performance measured by return on assets (*ROA*). During the three-year window before the sorting year, the average *ROA* decreases by 0.85% for unproductive firms, but increases by 0.70% for productive ones. The 1.56% of divergence in operating performance is significant (t-stat = 7.93). During the three-year window after the sorting year, average operating performance increases by 0.35% for unproductive firms, but decreases by 0.58% for productive firms. The 0.93% of convergence in productivity is significant (t-stat = 10.09). Approximately 60% (= 0.93%/1.56%) of the initial divergence is subsequently recovered. The convergence in average operating performance between productive and unproductive firms after the sorting year is shown in Panels A and B of Fig. 3.

These dynamics suggest that if investors chase recent performance without adequately considering the potential reversal, they may be overly optimistic (pessimistic) about the future prospects of productive (unproductive) firms (Kahneman et al., 1982).

[17] Hsu (2009) uses a real business cycle model and presents empirical evidence to show the relation between aggregate technological shocks and future market returns.

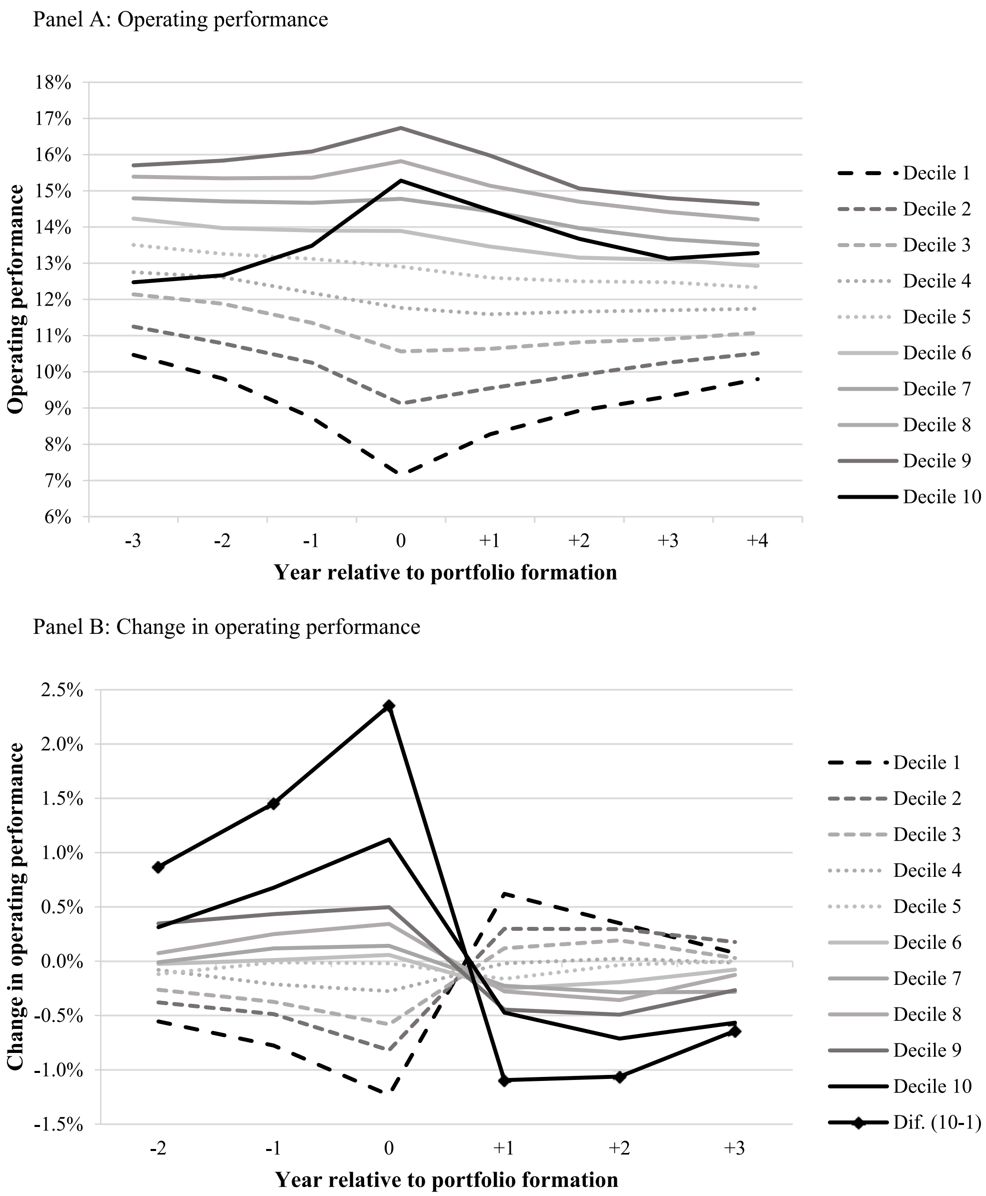

Fig. 3. Operating performance and year-to-year change in operating performance in event time. At the end of June every year, we sort firms into 10 portfolios based on firm productivity score. Decile 1 contains firms with the lowest productivity score (unproductive firms). Decile 10 contains firms with the highest productivity score (productive firms). Dif. (10-1) is the difference between deciles 10 and 1. Panels A and B plot the time-series averages of the median operating performance and year-to-year change in operating performance, respectively, for each of the deciles in event time. Operating performance is measured by operating income before extraordinary items scaled by total assets. Year 0 is the sorting year.

Consistent with this premise, Fig. 4 shows that before the sorting year, productive firms experience continuous price run-ups along the positive productivity and performance shocks, but unproductive firms experience persistently low returns. Furthermore, the returns reverse following the sorting year as the fundamental shocks reverse.

Panel C of Table 4 reports that during the three-year window before the sorting year, the average annual buy-and-hold return is 31.38% for productive firms, but only 1.83% for unproductive firms. During the three-year window after the sorting year, the average annual buy-and-hold return is 7.39% for productive firms and 21.18% for unproductive firms. Around 47% (= 13.79%/29.55%) of the pre-sorting return spread is subsequently reversed.

Taken together, the results indicate that the higher future returns on unproductive firms in excess of productive ones are consistent with the corrections of investors' earlier overreactions to firm productivity and operating performance due to extrapolation bias.

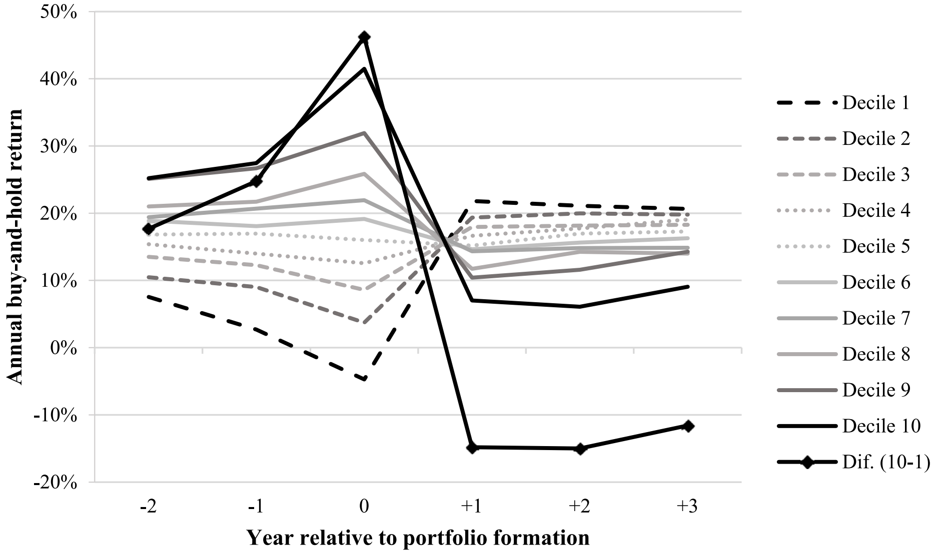

Fig. 4. Annual buy-and-hold returns in event time. At the end of June every year, we sort firms into 10 portfolios based on firm productivity score. Decile 1 contains firms with the lowest productivity score (unproductive firms). Decile 10 contains firms with the highest productivity score (productive firms). Dif. (10-1) is the difference between deciles 10 and 1. This figure plots the time-series averages of the equal-weighted annual buy-and-hold returns for each of the deciles in event time. Year 0 is the sorting year.

Table 5
Earnings announcement returns and earnings surprises of firm productivity portfolios.
At the end of June every year, we sort stocks into 10 portfolios based on the firm productivity score (*PROD*). The equal-weighted portfolios are rebalanced every year. Panel A reports the average earnings announcement returns (*EAR*) and non-announcement returns (Non-*EAR*) during the holding period. *EAR* is the market-adjusted daily stock returns within the three-day windows surrounding earnings announcements. Non-*EAR* is the adjusted daily returns on days outside the announcement windows. Panel B reports the average annual buy-and-hold return. Panel C reports the average earnings surprises for the holding period. Earnings surprise is quarterly actual earnings per share in quarter t minus expected earnings per share, scaled by stock price in quarter t. Expected earnings per share is the earnings per share in quarter t-4. The sample period is from July 1973 through June 2015. (10-1) is the difference between *PROD* deciles 10 and 1. Dif. is the difference between *EAR* and Non-*EAR*. The *t*-statistics (*t*-stat) are in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels.

PROD	1 (Low)	2	3	4	5	6	7	8	9	10 (High)	(10 − 1)	(*t*-stat)
Panel A: Average daily abnormal returns (%) during earnings announcements versus otherwise												
EAR	0.224	0.204	0.135	0.120	0.096	0.083	0.097	0.041	0.000	−0.059	−0.283***	(−6.28)
Non-*EAR*	0.126	0.072	0.057	0.051	0.040	0.035	0.029	0.020	0.022	0.014	−0.113***	(−8.61)
Diff	0.098***	0.132***	0.078***	0.070***	0.056***	0.049**	0.068***	0.021	−0.021	−0.072***	−0.170***	(−4.39)
	(2.84)	(4.36)	(3.11)	(3.76)	(2.83)	(2.54)	(4.40)	(1.08)	(−1.05)	(−3.14)		
Panel B: Annual buy-and-hold returns (%)												
	23.10***	20.50***	19.00***	17.70***	16.10***	15.80***	15.40***	12.80***	11.50***	8.10**	−15.00***	
	(4.97)	(5.17)	(4.86)	(4.93)	(4.82)	(4.59)	(4.42)	(3.91)	(3.33)	(2.05)	(−5.60)	
Panel C: Earnings surprises												
	0.013**	−0.002	−0.005	−0.004*	−0.005**	−0.006***	−0.007**	−0.003**	−0.004**	−0.006**	−0.019***	
	(2.40)	(−0.63)	(−1.46)	(−1.97)	(−2.50)	(−2.61)	(−2.59)	(−2.47)	(−2.20)	(−2.24)	(−5.34)	

4.3. *Expectation errors: Earnings announcement returns and earnings surprises*

La Porta et al. (1997) suggest that expectation error and mispricing should be corrected disproportionately when value-relevant information is released, such as when earnings are announced. If the firm productivity effect contains extrapolative mispricing, we should observe productive (unproductive) firms to have low (high) returns around earnings announcements, when investors are surprised by the realization of firm performance that is contrary to their expectations. A non-trivial part of the productivity effect should cluster around these information events. This price correction should be contemporaneous with the period with the acute reversals in operating performance, productivity, and stock returns (see Table 4 and Figs. 2 to 4).

We measure earnings announcement returns (*EAR*) as the market-adjusted daily stock returns within the three-day window around earnings announcements during the holding period. Panel A of Table 5 reports the time-series averages of equal-weighted *EAR* and non-*EAR* (market-adjusted returns on trading days outside of the announcement windows) on the decile portfolios sorted by *PROD*. Unproductive firms experience positive *EAR* (0.224%), but productive firms experience negative *EAR* (−0.059%). The *EAR* spread (−0.283% per day, *t*-stat = −6.28) is almost three times the difference in non-*EAR* between productive and unproductive firms (−0.113%). This *EAR* spread is stronger than the non-*EAR* spread by −0.170% per day (*t*-stat = −4.39). The discrepancy is

Table 6
Arbitrage costs and the firm productivity effect.
Panels A to D report the average returns (%) on equal-weighted portfolios independently sorted by quintiles of firm productivity score (*PROD*) and quintiles of an arbitrage costs measure. The arbitrage cost measures (*ArbCost*) are idiosyncratic stock return volatility (*IVOL*), effective bid–ask spread (*BIDASK*), the Amihud (2002) price impact (*ILLIQ*), and inverse of dollar trading volume (1/*DVOL*). The portfolios are rebalanced at the end of June every year. Monthly portfolio returns are from July of the sorting year through June of the following year. (5-1) is the difference between *PROD* quintiles 5 and 1. Panel E reports the coefficients from monthly Fama–MacBeth regressions of future stocks returns on *PROD*, *ArbCost*, the interaction of *PROD* and *ArbCost*, and controls. ln(*ME*) is the log of market equity, ln(*B*/*M*) is the log of the book-to-market ratio, *P6MRET* is past six-month return, and *P1MRET* is past one-month return. The sample period is from July 1973 through June 2015. The *t*-statistics in parentheses are corrected for autocorrelation using the Newey and West (1987) standard errors with 12 lags. ***, ** and * denote significance at the 1%, 5% and 10% levels.

Panel A: Portfolios sorted by firm productivity score and idiosyncratic stock return volatility

PROD	IVOL				
	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
(5 − 1)	−0.30*	−0.51***	−0.53***	−1.11***	−1.75***
	(−1.88)	(−3.10)	(−2.74)	(−6.49)	(−9.63)

Panel B: Portfolios sorted by firm productivity score and effective bid–ask spreads

PROD	BIDASK				
	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
(5 − 1)	−0.65***	−0.43**	−0.68***	−0.63***	−1.51***
	(−3.81)	(−2.51)	(−3.60)	(−3.16)	(−7.07)

Panel C: Portfolios sorted by firm productivity score and price impact

PROD	ILLIQ				
	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
(5 − 1)	−0.28	−0.18	−0.70***	−0.98***	−1.16***
	(−1.39)	(−1.01)	(−3.92)	(−5.46)	(−5.92)

Panel D: Portfolios sorted by firm productivity score and inverse of dollar trading volume

PROD	1/*DVOL*				
	1 (Low)	2	3	4	5 (High)
1 (Low)	1.14	1.20	1.44	1.81	2.01
2	1.28	1.32	1.39	1.61	1.75
3	1.12	1.29	1.44	1.42	1.56
4	1.06	1.19	1.15	1.30	1.25
5 (High)	0.96	0.83	0.82	0.90	0.94
(5 − 1)	−0.18	−0.37*	−0.63***	−0.91***	−1.08***
	(−0.89)	(−1.93)	(−3.53)	(−5.20)	(−5.97)

Panel E: Fama–MacBeth regressions

ArbCost		Intercept	*PROD*	*ArbCost*	*PROD*×*ArbCost*	ln(*ME*)	ln(*B*/*M*)	*P6MRET*	*P1MRET*
IVOL	Model 1	2.237**	−0.378	0.786***	−1.250***	−0.074**	0.051	0.656***	−0.051***
		(2.39)	(−0.30)	(5.27)	(−6.02)	(−2.17)	(0.42)	(3.57)	(−7.88)
BIDASK	Model 2	2.441***	−0.952	0.693***	−1.047***	−0.051	0.057	0.672***	−0.054***
		(2.65)	(−0.68)	(3.04)	(−3.33)	(−1.30)	(0.50)	(3.68)	(−8.35)
ILLIQ	Model 3	4.268***	−3.984***	3.242	−1.904	0.002	0.100	0.594***	−0.053***
		(4.07)	(−3.29)	(0.76)	(−0.32)	(0.05)	(0.73)	(2.98)	(−7.83)
1/*DVOL*	Model 4	4.360***	−3.968***	−0.000	0.000	−0.006	0.120	0.608***	−0.053***
		(4.34)	(−3.57)	(−1.17)	(0.92)	(−0.12)	(0.89)	(3.04)	(−7.80)

driven by both productive and unproductive firms, given that the difference between *EAR* and non-*EAR* is 0.098% (t-stat = 2.84) for unproductive firms and −0.072% (t-stat = −3.14) for productive firms.

For comparison, Panel B of Table 5 reports the time-series averages of annual buy-and-hold returns on the *PROD* portfolios. The difference in return between productive and unproductive firms is −15.0%. Hence, the magnitude of stock price adjustments around earnings announcements during the holding period (−3.396% = −0.283% per day × 3 days per quarter × 4 quarters per year) is 23% (3.396%/15.0%) of the annual buy-and-hold return spread. These findings suggest that investors extrapolate a firm's past productivity and its associated operating performance, but they are surprised by the good (bad) news in earnings released by underpriced unproductive (overpriced productive) firms.

Further, we examine the average earnings surprise on the *PROD* portfolios using a non-return based measure. Following Livnat and Mendenhall (2006), we define earnings surprise as quarterly actual earnings per share in quarter t minus expected earnings per share, scaled by the stock price in quarter t. We adopt the rolling seasonal random walk model, where the expected earnings per share is the earnings per share in quarter t-4. Panel C of Table 5 shows that productive firms have an average earnings surprise of −0.006 (t-stat = −2.24) and unproductive firms have an average earnings surprise of 0.013 (t-stat = 2.40). The difference in earnings surprise between the two groups of firms is −0.019 (t-stat = −5.34). The patterns of earnings surprise suggest that investors extrapolate the earnings per share for both underpriced unproductive and overpriced productive firms too far into the future and are surprised by the unexpected earnings. The finding is consistent with the patterns in earnings announcement returns and the reversals in firm-level productivity, operating performance, and stock returns.

4.4. The effect of firm-level arbitrage costs

Arbitrage trading can be risky and unprofitable due to noise traders' adverse demand shocks (De Long et al., 1990), capital constraints and career concerns (Shleifer and Vishny, 1997), and transaction costs (Pontiff, 2006). When arbitrage costs outweigh arbitrage benefits, mispricing is perpetuated because of the delay in price correction process. If extrapolative mispricing plays a role in the firm productivity effect, then the effect should be stronger when arbitrage costs are higher.

We examine how the firm productivity effect varies with four measures of arbitrage costs. First, we use idiosyncratic stock return volatility (*IVOL*) as a proxy of arbitrage risk (e.g., Ali et al., 2003; Lipson et al., 2011). Following Ang et al. (2006), we compute *IVOL* as the standard deviation of the residuals from the time-series regression of daily stock returns on the daily Fama and French (1993) three factors during the previous month before portfolio sorting. *IVOL* is an important concern in arbitrage because risk-averse arbitrageurs, who typically hold concentrated portfolios, prefer to hold less of the stocks with a high *IVOL* (for a given level of mispricing) due to hedging difficulties (Pontiff, 1996, 2006). Next, we measure transaction costs using the Amihud (2002) price impact (*ILLIQ*) measure, effective bid–ask spread (*BIDASK*), and the inverse of dollar trading volume (1/*DVOL*). *ILLIQ* is the time-series average of the ratio of the absolute value of daily stock returns to the daily dollar trading volume during the previous year. It measures the impact of order flow on stock prices. *BIDASK* is the time-series average of daily closing effective bid–ask spread during the previous year. It represents the trading expenses that compensate market makers for providing liquidity. *DVOL* is the time-series average of the product of the daily number of shares traded and daily stock price during the previous year. It inversely measures the price pressure and the time required to fill an order or to trade a large block of shares.

Panels A to D of Table 6 report the returns of the portfolios independently sorted by quintiles of *PROD* and quintiles of an arbitrage costs. There are two important patterns. First, the firm productivity effect strengthens as one moves from the quintile with low to the quintile with high arbitrage costs. For instance, the average return spread between high and low productivity firms monotonically decreases from −0.30% (t-stat = −1.88) when *IVOL* is low to −1.75% (t-stat = −9.63) when *IVOL* is high. Similar return spreads exist across portfolios sorted by each measure of transaction costs. Second, the firm productive effect is the strongest in the quintile with high arbitrage costs, but is weak or non-existent in the quintile with low arbitrage costs. These results indicate that severe arbitrage costs are necessary for the firm productivity effect.[18]

Panel E of Table 6 reports the regression coefficients from monthly Fama–MacBeth regressions of future stock returns on *PROD*, arbitrage costs, the interactions between *PROD* and arbitrage costs, and controls. When the arbitrage cost is *IVOL* (in Model 1), the interaction slope is negative and highly significant (coeff = −1.250; t-stat = −6.02). When the arbitrage cost is *BIDASK* (in Model 2), the interaction slope is also negative and significant (coeff = −1.047; t-stat = −3.33). In other words, the slope on *PROD* is more negative when *IVOL* or *BIDASK* is higher. Furthermore, the slope on *PROD* itself is no longer significant (i.e., the firm productivity effect vanishes) after accounting for the effect of these arbitrage costs. Consistent with the portfolio analysis, the firm productivity effect is stronger when these arbitrage costs are higher. The result points out the importance of arbitrage costs. However, the interaction slope is insignificant when the arbitrage cost is *ILLIQ* or *DVOL*. This might reflect the nonlinear roles of these arbitrage costs, which are detectable by non-parametric portfolio analysis, but not by linear cross-sectional regressions, in the firm productivity effect. Overall, the results in this section suggest that binding limits-to-arbitrage constraints, especially high *IVOL* or *BIDASK*, perpetuate the firm productivity effect.

[18] Robustness checks using other proxies for illiquidity, information uncertainty, and transaction costs, such as stock price, analyst coverage, and dispersion in analysts' earnings forecasts, yield qualitatively similar results. Fig. 4 and Panels A and B of Table A.2 in the online Supplementary Appendix show that the *PROD* return spread are slow to taper off, even in the second year after portfolio formation (t + 2). Panels C and D of Table A.2 show that the return spread is large in portfolios with high *ILLIQ* (a proxy for arbitrage costs), but it is insignificant in portfolios with low *ILLIQ*. High arbitrage costs seem to drive the slow convergence of the return spread to zero. We thank the referee for bringing up this observation.

Table 7
Adjustment costs and the firm productivity effect.
Panels A and B report the average returns (%) on equal-weighted portfolios independently sorted by quintiles of firm productivity score (*PROD*) and quintiles of an adjustment costs measure. The adjustment cost measures (*AdjCost*) are investment frictions (*IF*) and operating costs (*OC*). *IF* is a composite score based on firm age, total assets, and payout ratio. *OC* is the sum of cost of goods sold and selling, general, and administrative expense, scaled by total assets. The portfolios are rebalanced at the end of June every year. Monthly portfolio returns are from July of the sorting year through June of the following year. (5-1) is the difference between *PROD* quintiles 5 and 1. Panel C reports the coefficients from monthly Fama–MacBeth regressions of future stocks returns on *PROD*, *AdjCost*, the interaction of *PROD* and *AdjCost*, and controls. ln(*ME*) is the log of market equity, ln(*B/M*) is the log of the book-to-market ratio, *P6MRET* is past six-month return, and *P1MRET* is past one-month return. The sample period is from July 1973 through June 2015. The t-statistics in parentheses are corrected for autocorrelation using the Newey and West (1987) standard errors with 12 lags. ***, ** and * denote significance at the 1%, 5% and 10% levels.

Panel A: Portfolios sorted by firm productivity score and investment frictions

PROD	IF				
	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
(5 – 1)	−0.22	−0.58***	−0.77***	−0.98***	−1.56***
	(−1.19)	(−3.44)	(−4.84)	(−5.53)	(−8.14)

Panel B: Portfolios sorted by firm productivity score and operating costs

PROD	OC				
	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
(5 – 1)	−0.74***	−0.90***	−1.10***	−0.96***	−0.88***
	(−4.14)	(−5.13)	(−6.50)	(−5.07)	(−4.87)

Panel C: Fama–MacBeth regressions

AdjCost		Intercept	*PROD*	*AdjCost*	*PROD*×*AdjCost*	ln(*ME*)	ln(*B/M*)	*P6MRET*	*P1MRET*
IF	Model 1	−0.165	2.591**	0.092***	−0.128***	−0.070*	0.031	0.686***	−0.052***
		(−0.16)	(1.98)	(5.43)	(−5.98)	(−1.80)	(0.29)	(3.68)	(−8.05)
OC	Model 2	4.351***	−4.074***	0.129	−0.039	−0.024	0.090	0.488***	−0.048***
		(4.66)	(−3.90)	(0.58)	(−0.13)	(−0.61)	(0.96)	(3.83)	(−11.33)

5. Revisiting the risk-based explanations for the firm productivity effect

5.1. The role of firm-level adjustment costs

Several studies emphasize the importance of adjustment costs and productivity shocks in explaining the cross-section of stock returns.[19] In particular, İmrohoroğlu and Tüzel's (2014) production-based asset pricing model implies that firm-level adjustment costs disproportionally affect the flexibility of unproductive firms in disinvesting their capital stock when they face adverse aggregate productivity shocks. Hence, unproductive firms carry a risk premium.[20] The reasoning suggests that higher adjustment costs should amplify the firm productivity effect.

To test this hypothesis, we measure adjustment costs by investment frictions (*IF*) and operating costs (*OC*). *IF* is the average percentile ranks of the inverse of firm age, total assets, and payout ratio. These input variables are commonly used proxies for investment frictions in the asset pricing literature (e.g., Li and Zhang, 2010; Lam and John Wei, 2011). Following Novy-Marx (2011), *OC* is the sum of cost of goods sold and selling, general, and administrative expenses scaled by total assets. *IF* (*OC*) reflects the frictions in adjusting external financing (business operations) to cope with changing capital stock.

Panels A and B of Table 7 report the returns on portfolios independently sorted by quintiles of *PROD* and quintiles of an adjustment cost. The average return difference between high and low productivity firms monotonically decreases from −0.22% (t-stat = −1.19) when *IF* is low to −1.56% (t-stat = −8.14) when *IF* is high. Moreover, the return difference is the highest in the

[19] For example, Zhang (2005) argues that value stocks are riskier and therefore provide higher expected returns than growth stocks because the former face higher adjustment costs in reducing unproductive assets, particularly during economic downturns. Other studies include those by Livdan et al. (2009) on financial constraints and Jones and Tuzel (2013) on inventory growth.

[20] Moreover, proxies for adjustment costs are closely related to limits to arbitrage (e.g., Li and Zhang, 2010; Lam and John Wei, 2011). We have shown that limits to arbitrage accentuate the firm productivity effect.

Table 8
Distress risk and the firm productivity effect.
Panels A reports the average returns (%) on five-by-five portfolios sorted first by the Merton (1974) distance-to-default (*DD*) and then by firm productivity score (*PROD*). The equal-weighted portfolios are rebalanced at the end of June every year. Monthly portfolio returns are from July of the sorting year through June of the following year. (5-1) is the difference between *PROD* quintiles 5 and 1. AVG denotes the *PROD* portfolio return averaged over the distress risk quintiles. Panel B reports the coefficients from monthly Fama–MacBeth regressions of future stocks returns on *PROD*, *DD*, the interaction of *PROD* and *DD*, and controls. ln(*ME*) is the log of market equity, ln(*B/M*) is the log of the book-to-market ratio, *P6MRET* is past six-month return, and *P1MRET* is past one-month return. The sample period is from July 1973 through June 2015. The t-statistics in parentheses are corrected for autocorrelation using the Newey and West (1987) standard errors with 12 lags. ***, ** and * denote significance at the 1%, 5% and 10% levels.

Panel A: Controlling for distance-to-default

PROD	DD					
	1 (Low)	2	3	4	5 (High)	AVG
1 (Low)	1.45	1.63	1.64	1.86	1.92	1.70
2	1.39	1.49	1.62	1.62	1.75	1.57
3	1.28	1.38	1.39	1.40	1.64	1.42
4	1.08	1.13	1.30	1.21	1.33	1.21
5 (High)	1.00	0.88	0.83	0.79	0.94	0.88
(5 − 1)	-0.45^{**}	-0.75^{***}	-0.81^{***}	-1.08^{***}	-0.98^{***}	-0.82^{***}
	(−2.38)	(−5.45)	(−5.30)	(−7.52)	(−6.07)	(−6.64)

Panel B: Fama–MacBeth regressions

	Intercept	*PROD*	DD	PROD×*DD*	ln(*ME*)	ln(*B/M*)	P6MRET	*P1MRET*
DD	4.652^{***}	-4.186^{***}	-1.795^{*}	0.638	−0.034	0.096	0.461^{***}	-0.048^{***}
	(4.67)	(−3.61)	(−1.69)	(0.34)	(−0.84)	(0.78)	(3.07)	(−7.81)

quintile with high *IF*. However, the return difference is similar across the *OC* quintiles. The return difference is −0.74% (t-stat = −4.14) when *OC* is low and is −0.88% (t-stat = −4.87) when *OC* is high.

Panel C of Table 7 reports the results from Fama–MacBeth regressions. In Model 1, when the adjustment cost is *IF*, the interaction slope between *PROD* and the adjustment cost is negative and significant (coeff = −0.128; t-stat = −5.98). In Model 2, when the adjustment cost is *OC*, the interaction slope is insignificant (coeff = −0.039; t-stat = −0.13). Similar to the portfolio sorts, the regression results indicate that the firm productivity effect varies with *IF*, but not with *OC*. The results suggest that inflexibility in adjusting external financing to cope with changing capital stock, rather than operating leverage, plays some role in the firm productivity effect.

5.2. The role of firm-level distress risk

Unproductive firms face higher distress risk than productive firms, as reflected by the distress risk measures in Table 2. Nguyen and Swanson (2009) and İmrohoroğlu and Tüzel (2014) also find that unproductive firms are more likely to be delisted due to financial distress than productive firms. The higher stock returns on unproductive firms relative to productive firms may simply compensate for their higher distress risk (e.g., Vassalou and Xing, 2004). If this is the case, the firm productivity effect should disappear or at least be substantially weakened after controlling for distress risk.

Panel A of Table 8 reports the returns on the 5 × 5 portfolios sorted first by Merton's (1974) distance-to-default measure (*DD*) and then by *PROD*. The firm productivity effect strengthens as we move from the quintile with low to the quintile with high *DD*. The average return spread between high and low productivity firms is −0.45% (t-stat = −2.38) in the portfolio with low *DD*, compared to −0.98% (t-stat = −6.07) in the portfolio with high *DD*. The return spread between high and low *PROD* among firms with the highest distress risk is more than twice as large as that in firms with the lowest distress risk. When we control for financial distress by averaging the returns of each *PROD* portfolio over distress risk quintiles in the last column (AVG), the return spread between the high and low productivity firms decreases, but remains significant. Furthermore, Panel B shows that the predictive power of *PROD* remains similar when we include distress risk and the interaction between *PROD* and distress risk in the Fama–MacBeth regressions of future stock returns on *PROD*. The slope on *PROD* is −4.186 (t-stat = −3.61.).[21] Taken together, these findings suggest that distress risk only plays a minor role in the firm productivity effect.[22]

5.3. The role of economic downturn[23]

In İmrohoroğlu and Tüzel's (2014) model, unproductive firms' returns covary more with changing economic conditions in recessions and when there is negative aggregate productivity shocks. In this section, we examine the role of economic downturn

[21] Table A.3 of the online Supplementary Appendix shows that the results are qualitatively similar using other proxies for distress risk.

[22] Griffin and Lemmon (2002) study the effect of distress risk on the value premium. They also conclude that the value effect is more consistent with the mispricing hypothesis than the risk explanation. Franzen et al. (2007) show how R&D firms' distress risk can be misspecified. 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. Unreported tests indicate that the firm productivity effect still exists after we remove distressed firms with junk bond ratings from our sample.

[23] We thank the referee for suggesting this test.

Table 9
Economic downturns and the firm productivity effect.
Panels A presents the average return spread (%) between the top and bottom quintile portfolios sorted on *PROD*, conditioned on recession months. Our indicator of recession follows the definition of National Bureau of Economic Research (NBER). Panels B to D report the average returns (%) on portfolios cross-sorted by quintiles of firm productivity score (*PROD*) and quintiles of a variable on interest, which includes *IVOL*, *BIDASK*, *ILLIQ*, 1/*DVOL*, *IF*, *OC*, and *DD*, conditioned on recession months. *IVOL* is idiosyncratic stock return volatility, *BIDASK* is effective bid–ask spread, *ILLIQ* is the Amihud (2002) price impact, and 1/*DVOL* is the inverse of dollar trading volume. *IF* is a composite score based on firm age, total assets, and payout ratio. *OC* is the sum of cost of goods sold and selling, general, and administrative expense, scaled by total assets. *DD* is the Merton (1974) distance-to-default. The portfolios are rebalanced at the end of June every year. Monthly portfolio returns are from July of the sorting year through June of the following year. Portfolio returns are equal-weighted. The sample period is from July 1973 through June 2015. The *t*-statistics in parentheses are corrected for autocorrelation using the Newey and West (1987) standard errors with 12 lags. ***, ** and * denote significance at the 1%, 5% and 10% levels.

Panel A: Sub-sample analysis — recession		
	Recession		
	Yes	No	Diff
Average return spread (%)	−1.21***	−1.19***	−0.02
t-stat	(−2.36)	(−7.52)	(−0.03)
Number of months	78	426	

Panel B: Recession and arbitrage costs						
Recession	(i) *IVOL*					
	1 (Low)	2	3	4	5 (High)	(5 − 1)
Yes	−0.20	−0.24	−0.37	−1.10***	−1.80***	−1.60**
	(−0.46)	(−0.81)	(−0.76)	(−3.70)	(−4.36)	(−2.11)
No	−0.32*	−0.55***	−0.56***	−1.11***	−1.74***	−1.43***
	(−1.94)	(−3.07)	(−2.84)	(−5.32)	(−8.09)	(−6.03)
Recession	(ii) *BIDASK*					
	1 (Low)	2	3	4	5 (High)	(5 − 1)
Yes	−0.61	−0.80*	−0.49	−0.45	−1.12***	−0.51
	(−0.82)	(−1.75)	(−1.45)	(−0.87)	(−3.20)	(−0.41)
No	−0.66***	−0.36**	−0.72***	−0.66***	−1.58***	−0.92***
	(−3.93)	(−2.06)	(−3.33)	(−2.87)	(−6.48)	(−2.80)
Recession	(iii) *ILLIQ*					
	1 (Low)	2	3	4	5 (High)	(5 − 1)
Yes	−0.14	−0.64	−0.82***	−0.55*	−0.51	−0.36
	(−0.34)	(−1.13)	(−3.38)	(−1.67)	(−0.97)	(−0.58)
No	−0.31	−0.10	−0.68***	−1.06***	−1.28***	−0.98***
	(−1.47)	(−0.55)	(−3.33)	(−5.66)	(−6.26)	(−3.69)
Recession	(iv) 1/*DVOL*					
	1 (Low)	2	3	4	5 (High)	(5 − 1)
Yes	−0.46	−1.16*	−0.41	−0.27	−0.76*	0.30
	(−0.96)	(−1.83)	(−1.50)	(−0.75)	(−1.70)	(0.41)
No	−0.13	−0.23	−0.66***	−1.03***	−1.13***	1.01***
	(−0.59)	(−1.24)	(−3.42)	(−5.70)	(−6.08)	(3.46)
Panel C: Recession and adjustment costs						
Recession	(i) *IF*					
	1 (Low)	2	3	4	5 (High)	(5 − 1)
Yes	−0.27	−0.48	−0.46	−1.32***	−1.43***	−1.16***
	(−0.51)	(−1.07)	(−1.49)	(−3.22)	(−4.86)	(−2.65)
No	−0.21	−0.60***	−0.83***	−0.92***	−1.58***	−1.37***
	(−1.21)	(−3.50)	(−4.94)	(−4.72)	(−6.71)	(−5.68)
Recession	(ii) *OC*					
	1 (Low)	2	3	4	5 (High)	(5 − 1)
Yes	−0.77**	−1.03***	−1.00***	−0.64	−0.46	0.31
	(−2.20)	(−2.69)	(−3.54)	(−1.38)	(−1.02)	(0.79)

(*continued on next page*)

Table 9 (*continued*).

No	−0.73***	−0.88***	−1.12***	−1.02***	−0.96***	−0.23
	(−3.75)	(−4.38)	(−5.63)	(−4.97)	(−5.37)	(−1.21)
Panel D: Recession and distress risk						
Recession	DD					
	1 (Low)	2	3	4	5 (High)	(5 − 1)
Yes	−0.67*	−0.53	−0.73**	−1.46***	−0.41	0.25
	(−1.70)	(−1.65)	(−2.03)	(−4.39)	(−0.61)	(0.32)
No	−0.41**	−0.80***	−0.83***	−1.00***	−1.08***	−0.67***
	(−1.98)	(−4.82)	(−5.24)	(−6.33)	(−6.69)	(−3.72)

on the firm productivity effect. We partition our sample based on recession months as defined by the National Bureau of Economic Research (NBER). Panel A of Table 9 shows that the average *PROD* return spreads are almost identical (−1.2% a month) whether there is economic recession. Furthermore, we test the combined impacts on the *PROD* return spread from economic recession and one of the following drivers: arbitrage costs, adjustment costs, and distress risk. Panels B to D report the average return spread in *PROD* on portfolios cross-sorted by quintiles of *PROD* and quintiles of one of the abovementioned variables of interest, conditioned on economic recession. Contrary to the prediction from İmrohoroğlu and Tüzel (2014) model, the *PROD* return spreads are generally larger, especially in portfolios with high arbitrage costs, adjustment costs, or distress risk, in non-recession months than in recession months. Moreover, the difference in average *PROD* return spread (Diff) between high and low levels of arbitrage costs, adjustment costs, or distress risk is generally larger in non-recession months than in recession months. For example, the difference in average *PROD* return spread for the *BIDASK* portfolios is −0.92 (t-stat = −2.80) in non-recession months, but it is only −0.51 (t-stat = −0.41) in recession months.[24] Our results suggest that high arbitrage cost, adjustment cost, or distress risk during economic downturns when investors (firms) face difficulties in liquidating their positions (disinvesting) are not the force to drive the firm productivity effect.

5.4. The productivity effect: factor versus characteristic[25]

Apart from the specific risk-related drivers of the firm productivity effect suggested by Nguyen and Swanson (2009) and İmrohoroğlu and Tüzel (2014), we test whether a firm's exposure to productivity risk (a *PROD* risk factor) explains future returns. Following Daniel and Titman (1997), we use a stock's preformation factor loading to estimate the expected *PROD* loading, β_{PROD}. Specifically, we regress individual firm's stock returns on the preformation *PROD* factor over the 42- to 7-month period before portfolio formation. The *PROD* factor is the monthly average portfolio return spread between the decile portfolios with the highest and lowest *PROD*. Panel A of Table 10 reports the portfolio returns sorted by β_{PROD}. Similar to *PROD*, there is a negative monotonic relation between β_{PROD} and portfolio returns. The return spread is −0.39 (t-stat = −2.21).

Next, we test whether a *PROD* risk factor or a *PROD* characteristic better explains the cross-section of returns. We independently sort stocks into 5 × 5 portfolios based on their β_{PROD} and *PROD* scores. Panel B of Table 10 shows that the *PROD* score still explains returns after controlling for β_{PROD}. The return spreads in the *PROD* score are all significant and they range from −0.68 to −1.18. In contrast, the return spreads in β_{PROD} are small and mostly insignificant after controlling for the *PROD* score. The result implies that the firm productivity effect is not related to exposure to productivity risk. Overall, our tests suggest that risk-based explanations do not play a large role in explaining the firm productivity effect.[26]

6. Decomposing the firm productivity effect

So far, we have studied the drivers of the firm productivity effect related to the extrapolation of past productivity, operating performance, and returns, as well as limits to arbitrage and adjustment costs, in isolation. Standard portfolio sorts and cross-sectional regressions yield supportive results. However, we are still unclear about the relative strength and importance of each class of variables in driving the return predictability of firm productivity (*PROD*).

In this section, we evaluate the fraction of the firm productivity effect that is explained by a candidate variable alone or a group of candidates after controlling for all other competing candidates in a unified framework that allows for a direct comparison across different variables. We follow Hou and Loh's (2016) decomposition algorithm. It has the advantage of quantifying the contribution of a candidate variable in explaining the firm productivity effect even when the candidate is subsumed by *PROD* in cross-sectional regressions.

[24] We also use an alternative measure for economic downturn. We partition our sample into two groups based on the aggregate industrial production growth rate. The results are qualitatively similar. See Supplementary Appendix Table A.4.

[25] We thank the referee for suggesting this test.

[26] We rerun all of the analyses using an alternative measure of firm-level productivity (the *TFP* measure) sourced from İmrohoroğlu and Tüzel (2014). Tables A.5 to A.12 and Figs. A.1 to A.4 in the online Supplementary Appendix show that the results based on *TFP* are qualitatively similar to (although weaker than) those based on *PROD*. In unreported tables, we adjust our returns with the Fama and French (2015) five-factor model, augmented with the Carhart (1997) momentum factor in all portfolio sorts. We also include stocks priced below $1. Our findings remain quantitatively similar.

Table 10
The productivity effect: characteristic versus factor.
Panel A reports the average returns (%) on equal-weighted portfolios sorted by a firm's exposure to productivity risk (β_{PROD}). We use a stock's preformation factor loadings to estimate the expected *PROD* loading, β_{PROD}. We regress individual firm's stock returns on the preformation *PROD* factor over the 42- to 7-month period before portfolio formation. The *PROD* factor is the portfolio return spread between the decile portfolios with the highest and lowest *PROD*. Panel B reports the average returns (%) on equal-weighted portfolios independently sorted by quintiles of firm productivity score (*PROD*) and quintiles of β_{PROD}. The sample period is from July 1973 through June 2015. The *t*-statistics in parentheses are corrected for autocorrelation using the Newey and West (1987) standard errors with 12 lags. ***, ** and * denote significance at the 1%, 5% and 10% levels.

Panel A: Portfolios sorted by exposure to productivity risk (β_{PROD})

β_{PROD}	1 (Low)	2	3	4	5 (High)	(5 − 1)
RET	1.60***	1.49***	1.43***	1.37***	1.21***	−0.39**
	(5.03)	(5.81)	(5.95)	(5.46)	(3.69)	(−2.21)

Panel B: Portfolios sorted by exposure to productivity risk (β_{PROD}) and firm productivity score (*PROD*)

PROD	β_{PROD}					
	1 (Low)	2	3	4	5 (High)	(5 − 1)
1 (Low)	2.13	1.91	1.81	1.85	1.81	−0.32
2	1.69	1.46	1.51	1.55	1.48	−0.22
3	1.54	1.45	1.41	1.38	1.21	−0.33*
4	1.30	1.27	1.28	1.25	1.16	−0.14
5 (High)	0.95	1.15	1.13	1.07	0.81	−0.14
(5 − 1)	−1.18***	−0.77***	−0.68***	−0.78***	−1.00***	0.18
	(−6.68)	(−4.69)	(−3.63)	(−4.18)	(−5.53)	(0.82)

In stage one, we estimate the following monthly Fama–MacBeth cross-sectional regressions:

$$ARET_{it} = \alpha_t + \beta_t PROD_{it-1} + \tilde{\varepsilon}_{it}, \tag{3}$$

where $ARET_{it}$ is firm *i*'s characteristic-adjusted stock return, computed according to Daniel et al. (1997).[27] In stage two, we add a candidate variable or a set of candidates ($Candidate_{it-1}$):

$$ARET_{it} = \tilde{\alpha}_t + \tilde{\beta}_t^R PROD_{it-1} + \tilde{\beta}_t^C Candidate_{it-1} + \tilde{\varepsilon}_{it}. \tag{4}$$

This specification allows us to assess the power and robustness of *PROD* in predicting future stocks returns in the presence of the candidate variable(s). In stage three, we regress *PROD* on the candidate variable(s):

$$PROD_{it-1} = a_{t-1} + \delta_{t-1} Candidate_{it-1} + \omega_{it-1}. \tag{5}$$

This stage reveals the relation between *PROD* and the candidate variable(s). A candidate that has the potential to explain the firm productivity effect should be correlated with *PROD*.

In stage four, we use the linearity of covariance to decompose the estimated slope (β_t) from Eq. (3) into two components:

$$\begin{aligned}\beta_t &= \frac{Cov\left(ARET_{it}, PROD_{it-1}\right)}{Var\left(PROD_{it-1}\right)} = \frac{Cov\left(ARET_{it}, (a_{t-1} + \delta_{t-1} Candidate_{it-1} + \omega_{it-1})\right)}{Var\left(PROD_{it-1}\right)} \\ &= \frac{Cov\left(ARET_{it}, \delta_{t-1} Candidate_{it-1}\right)}{Var\left(PROD_{it-1}\right)} + \frac{Cov\left(ARET_{it}, (a_{t-1} + \omega_{it-1})\right)}{Var\left(PROD_{it-1}\right)} \\ &= \beta_t^C + \beta_t^{\varepsilon},\end{aligned} \tag{6}$$

where β_t^C/β_t measures the fraction of the firm productivity effect explained by the candidate variable(s) and $\beta_t^{\varepsilon}/\beta_t$ measures the fraction left unexplained. Specifically, β_t^C is related to δ_{t-1} in the following way[28]: Furthermore, β_t^C is associated with $\tilde{\beta}_t^C$ and $\tilde{\beta}_t^R$ in Eq. (4) as follows.

$$\beta_t^C = \left(\frac{\tilde{\beta}_t^C}{\delta_{t-1}} + \tilde{\beta}_t^R\right) \frac{Var\left[\delta_{t-1} Candidate_{it-1}\right]}{Var\left[PROD_{it-1}\right]}. \tag{7}$$

[27] At the end of June each year, we sort all stocks using NYSE breakpoints. Within each market equity (*ME*) quintile, we sort stocks into quintiles according to the book-to-market equity ratio (*B/M*) from the previous fiscal year end. Within each *ME-B/M* intersection, we sort stocks into quintiles based on the past 12-month stock return skipping the latest month (*12MRET*). The characteristic-adjusted stock return is the raw stock return minus the value-weighted return on the *ME-B/M-12MRET* matched benchmark portfolio.

[28] A high correlation between *PROD* and a candidate variable does not guarantee that the candidate can explain a large fraction of the firm productivity effect: the part of the candidate related to *PROD* may not be the part of the candidate that explains the negative relation between *PROD* and returns. Specifically, Eq. (7) shows that β_t^c depends on both the fraction of the variation of *PROD* explained by the candidate variable ($\frac{Var[\delta_{t-1}Candidate_{it-1}]}{Var[PROD_{it-1}]}$) and the portion of the candidate variable that is uncorrelated with *PROD* but is correlated with stock returns ($\tilde{\beta}_t^C$) (see Hou and Loh, 2016).

Table 11

Decomposing the firm productivity effect.

There are four stages in the decomposition analysis. Stage one regresses adjusted stock returns (*ARET*) on firm productivity score (*PROD*). *ARET* is the characteristic-adjusted stock return, computed following Daniel et al. (1997). At the end of June each year, we sort all stocks using NYSE breakpoints. Within each market equity (*ME*) quintile, we sort stocks into quintiles according to the book-to-market ratio (*B/M*) from previous fiscal year end. Within each *ME-B/M* intersection, we sort stocks into quintiles based on the past 12-month stock return skipping the latest month (*12MPRET*). *ARET* is the raw stock return minus the value-weighted return on the *ME-B/M-12MPRET* matched benchmark portfolio. Stage two adds a set of candidate variables to the cross-sectional regression of stage one. Stage three regresses *PROD* on the set of candidate variables. Stage four decomposes the estimated *PROD* slope from stage one into two components, the part and fraction explained by the candidate variables (EXPLAINED) and the part and fraction left unexplained (RESID). The candidate variables are as follows. *3YΔPROD* is the average year-to-year change in *PROD* over the past three years, *3YΔROA* is average year-to-year change in return on assets over the past three years, *P3YRET* is average annual return over the past three years, *IVOL* is idiosyncratic stock return volatility, *BIDASK* is the effective bid–ask spread, *ILLIQ* is the Amihud (2002) price impact, *DVOL* is dollar trading volume, *IF* is investment frictions, and *OC* is operating costs. Panels A to C report the results from the decomposition using a single candidate variable in turn. Panel D reports the results from the decomposition using all 12 candidate variables simultaneously. The sample period is from July 1973 through June 2015. The *t*-statistics (*t*-stat) are in parentheses. The standard errors of the fractions are computed by the multivariate delta method. ***, ** and * denote significance at the 1%, 5% and 10% levels.

Panel A: Past productivity growth, operating performance growth or stock returns as individual candidate

Stage	Description	Coefficients	Candidate					
			3YΔPROD	*t*-stat	*3YΔROA*	*t*-stat	*P3YRET*	*t*-stat
1	*ARET* on *PROD*	Intercept	1.960***	(6.14)	3.084***	(9.93)	1.890***	(6.24)
		PROD	−2.377***	(−5.63)	−3.747***	(−9.29)	−2.283***	(−5.73)
2	*ARET* on *PROD*	Intercept	1.930***	(5.98)	3.116***	(10.69)	1.413***	(−3.19)
	and candidate	*PROD*	−2.334***	(−5.43)	−3.784***	(−10.00)	−1.540***	(−3.03)
		Candidate	−0.049	(−0.16)	0.003	(0.28)	−0.319**	(−2.03)
3	*PROD* on candidate	Intercept	0.745***	(460.85)	0.743***	(447.00)	0.731***	(356.64)
		Candidate	0.273***	(76.70)	0.001***	(5.79)	0.077***	(22.26)
		Adj. R^2	16.48%		0.87%		13.92%	
4	Decompose	EXPLAINED	−0.401		0.002		−0.751	
	Stage-1 coefficients		16.86%***	(2.72)	−0.06%	(−0.05)	32.88%***	(3.43)
		RESID	−1.976		−3.749		−1.532	
			83.14%***	(13.40)	100.06%***	(89.38)	67.12%***	(7.01)
	Observations (months)		2605		2287		2823	

Panel B: A measure of arbitrage cost as individual candidate

Stage	Description	Coefficients	Candidate							
			IVOL	*t*-stat	*BIDASK*	*t*-stat	*ILLIQ*	*t*-stat	*DVOL*	*t*-stat
1	*ARET* on *PROD*	Intercept	2.026***	(7.06)	2.021***	(7.04)	1.906***	(6.63)	1.906***	(6.63)
		PROD	−2.476***	(−6.65)	−2.470***	(−6.63)	−2.335***	(−6.23)	−2.335***	(−6.23)
2	*ARET* on *PROD*	Intercept	2.089***	(8.80)	1.797***	(7.42)	1.506***	(5.72)	1.856***	(6.00)
	and candidate	*PROD*	−2.389***	(−7.64)	−2.291***	(−6.56)	−1.853***	(−5.33)	−2.254***	(−5.49)
		Candidate	−0.080***	(−2.71)	0.004	(0.08)	1.979***	(2.73)	−0.000	(−0.45)
3	*PROD* on candidate	Intercept	0.757***	(492.85)	0.750***	(400.87)	0.750***	(418.49)	0.739***	(431.55)
		Candidate	−0.005***	(−11.17)	−0.002***	(−2.93)	−0.234***	(−7.48)	0.000***	(3.89)
		Adj. R^2	2.40%		0.77%		5.64%		4.92%	
4	Decompose	EXPLAINED	−0.143		−0.193		−0.583		−0.199	
	Stage-1 coefficients		5.78%	(0.89)	7.83%**	(2.26)	24.96%***	(4.23)	8.50%**	(2.57)
		RESID	−2.333		−2.277		−1.752		−2.136	
			94.22%***	(14.55)	92.17%***	(26.57)	75.04%***	(12.73)	91.50%***	(27.70)
	Observations (months)		3113		3114		2860		2860	

Panel C: A measure of adjustment cost as individual candidate

Stage	Description	Coefficient	Candidate			
			IF	*t*-stat	*OC*	*t*-stat
1	*ARET* on *PROD*	Intercept	2.029***	(6.19)	1.979***	(7.24)
		PROD	−2.480***	(−5.83)	−2.433***	(−6.77)
2	*ARET* on *PROD*	Intercept	1.755***	(7.14)	1.825***	(6.18)
	and candidate	*PROD*	−2.461***	(−5.80)	−2.402***	(−6.80)
		Candidate	0.006*	(1.74)	0.117**	(2.33)
3	*PROD* on candidate	Intercept	0.744***	(314.33)	0.743***	(394.86)
		Candidate	−0.000**	(−2.04)	0.001*	(1.74)
		Adj. R^2	0.20%		0.08%	
4	Decompose	EXPLAINED	−0.024		−0.035	
	Stage 1 coefficient		0.97%	(0.99)	1.45%**	(1.98)
		RESID	−2.456		−2.398	

(*continued on next page*)

Table 11 (*continued*).

Panel C: A measure of adjustment cost as individual candidate						
Stage	Description	Coefficient	Candidate			
			IF	*t*-stat	*OC*	*t*-stat
			99.03%***	(100.93)	98.55%***	(135.13)
	Observations (months)		3176		2861	

Panel D: All candidates simultaneously					
Stage	Description		Coefficient		*t*-stat
1	*ARET* on *PROD*	Intercept	3.148***		(8.72)
		PROD	−3.838***		(−8.17)
2	*ARET* on *PROD* and candidates	Intercept	0.477		(1.07)
		PROD	−1.352**		(−2.36)
		3Y ΔPROD	0.567**		(1.97)
		3Y ΔROA	0.017**		(2.08)
		P3YRET	−0.543***		(−3.54)
		IVOL	−0.039		(−0.93)
		BIDASK	0.262***		(3.82)
		ILLIQ	3.788***		(4.26)
		DVOL	−0.000		(−0.29)
		IF	0.002		(0.86)
		OC	0.105**		(2.01)
3	*PROD* on candidates	Intercept	0.732***		(329.29)
		3Y ΔPROD	0.194***		(22.40)
		3Y ΔROA	−0.000		(−0.97)
		P3YRET	0.039***		(10.95)
		IVOL	−0.003***		(−11.50)
		BIDASK	0.002***		(4.25)
		ILLIQ	−0.210***		(−6.82)
		DVOL	0.000***		(4.89)
		IF	0.000		(0.65)
		OC	0.002***		(4.38)
		Adj. R^2	30.89%		
				EXPLAINED	
4	Decompose Stage-1 coefficients	*3Y ΔPROD*	−0.453	11.82%***	(3.72)
		3Y ΔROA	−0.008	0.21%	(0.55)
		P3YRET	−0.743	19.37%***	(5.52)
		IVOL	−0.583	15.18%***	(5.41)
		BIDASK	0.228	−5.95%**	(−2.55)
		ILLIQ	−1.031	26.87%***	(8.66)
		DVOL	−0.352	9.18%***	(3.78)
		IF	0.036	−0.93%	(−1.1)
		OC	0.050	−1.29%	(−1.6)
		RESID	−0.980	25.55%***	(3.22)
	Observations (months)			2053	

We categorize the candidate variables into those related to past performance, limits to arbitrage, and adjustment costs in our analysis. We start by analyzing each candidate individually in Panels A through C of Table 11. The negative *PROD* slopes, ranging from −2.283 to −3.747, in stage one (Eq. (3)) are significant, confirming the negative relation between firm productivity and future stock returns. In stage two (Eq. (4)), as a candidate variable is added, the magnitudes of the *PROD* slopes slightly reduce. The slopes of the candidate variables *3YΔPROD*, *P3YRET*, *IVOL*, and *DVOL* are negative. These candidates predict negative future returns after controlling for *PROD*. However, the candidate variables *3YΔROA*, *BIDASK*, *ILLIQ*, *IF*, and *OC* predict positive returns.

Stage three (Eq. (5)) in Panel A of Table 11 shows that the candidate variables *3YΔPROD* and *P3YRET* (changes in past productivity and stock returns, respectively) are positively correlated with *PROD*. The corresponding adjusted R^2s indicate that each of these candidates explains approximately 15% of the variation in *PROD*. In contrast, Panels B and C show that the candidate variables related to arbitrage costs and adjustment costs are negatively related to *PROD* (apart from *DVOL* and *OC*). The results corroborate our earlier finding that the firm productivity effect is stronger in stocks with high investment frictions or limits to arbitrage. However, the corresponding adjusted R^2s are mostly below 6%, pointing to the weaker ability of these candidates in explaining the variation in *PROD*.

When we decompose the slope β_t (Eq. (6)) in stage four in Panel A of Table 11, we find that the candidate variables *3YΔPROD* and *P3YRET* explain 16.86% and 32.88%, respectively, of the firm productivity effect. Furthermore, the positive correlation between *PROD* and past performance in the stage three regressions imply that the part of past performance (*3YΔPROD* and *P3YRET*) that is related to *PROD* predicts future returns.[29] Together, these findings provide important support to the extrapolation of past-performance hypothesis in explaining the firm-productivity effect. In Panel B, we report the explanatory power of the candidate variables related to arbitrage costs. They range from 5.78% to 24.96%. In particular, *IVOL* and *ILLQ* have independent power in predicting returns (as shown by the stage two regressions) and they also explain the firm productivity effect through its negative relation with *PROD* (as shown by the stage three regressions). This result echoes the interpretation that limits to arbitrage perpetuate the firm-productivity effect. In contrast, despite the success in portfolio sorts and Fama–MacBeth regressions in Section 4, Panel C shows that the explanatory power of the candidate variables related to adjustment costs (*IF* and *OC*) is low (approximately 1%). The result casts doubt on the ability of adjustment costs to explain the firm productivity effect.

Panel D of Table 11 presents the results from the multivariate decomposition analysis of the marginal contribution of each of the nine candidate variables in the return predictability of *PROD*. The results from stage one to stage three are similar to those of the univariate decomposition analysis. The adjusted R^2 from stage three indicates that the full collection of candidates can replicate 30.89% of the variation in *PROD*. The results from stage four show that the candidate variables together explain 74.45% of the firm productivity effect. These candidates are rather effective in extracting the information contained in *PROD* that predicts returns. The candidate variables related to past productivity growth (*3YΔPROD*), operating performance (*3YΔROA*), and stock returns (*P3YRET*) explain 11.82% (t-stat = 3.72), 0.21% (t-stat = 0.55), and 19.37% (t-stat = 5.52), respectively, of the return predictability of *PROD*. Together, they explain 31.4% of the return predictability. However, the candidate variables related to adjustment costs (*IF* and *OC*) do not have significant explanatory power after controlling for other competing variables. In contrast, the fractions of the *PROD* slope explained by *IVOL*, *BIDASK*, *ILLIQ*, and *DVOL* are 15.18% (t-stat = 5.41), −5.95% (t-stat = −2.55), 26.87% (t-stat = 8.66), and 9.18% (t-stat = 3.78), respectively. Although the explanatory power of *BIDASK* has the wrong sign, this group of candidates related to arbitrage costs explains 45.28% of the negative relation between *PROD* and future returns.[30]

Overall, the decomposition analysis shows that extrapolative mispricing and limited arbitrage are more successful than capital adjustment costs in explaining the return predictability of firm productivity, leaving only 25.55% of the return predictability unexplained.[31]

7. Conclusion

Firm-level productivity is important in neoclassical investment-based asset pricing models as they explain the cross-sectional relation between stock returns and various firm characteristics, such as valuation ratios, investment rates, and past returns. Previous studies have found a negative relation between firm productivity and future stock returns (the firm productivity effect) and have attributed it to risk. In this study, we explore the role of mispricing (especially in the form of extrapolative errors) and limits to arbitrage in explaining the firm productivity effect.

Our finding shows that investors seem to have underpriced unproductive firms and overpriced productive firms. The mispricing of firm productivity, especially in overpriced productive firms, is more severe after periods with high investor sentiment when speculative trading is prevalent. The evidence is more consistent with short sale constraints and the overpricing of productive firms as at least a partial explanation for the mispricing. Further analyses show that investors appear to erroneously extrapolate past productivity growth and its associated performance, despite their subsequent reversals. The price correction associated with the mispricing of firm productivity occurs disproportionately around earnings announcements, reflecting investors' surprises to unexpected earnings. We also find that the mispricing is not exploited in a timely manner because of limits to arbitrage. Our decomposition analysis suggests that the extrapolation of past returns and past productivity growth and limits to arbitrage explain most of the firm productivity effect. In contrast, the rational explanation associated with adjustment costs, distress risk, or economic downturn appears to be very limited in explaining the firm productivity effect.

Given the close relation between firm productivity and many firm characteristics that predict stock returns, our findings have implications for the role of extrapolative expectation errors in explaining other asset pricing anomalies based on firm characteristics. The close link between extrapolative expectation and firm productivity – the key variable in many neoclassical models – also suggests the potential role of extrapolative expectation in a richer neoclassical model that incorporates behavioral biases, such as Hirshleifer et al. (2015).

CRediT authorship contribution statement

Tze Chuan 'Chewie' Ang: Methodology, Data curation, Software, Writing - original draft. **F.Y. Eric C. Lam:** Data curation, Validation, Writing - review & editing. **K.C. John Wei:** Conceptualization, Methodology, Supervision, Writing - review & editing.

[29] The significant $\tilde{\beta}_t^C$ in the stage two regression for the candidate variable *P3YRET* also suggests that part of the return predictability of *PROD* comes from *P3YRET*'s power to predict returns independently.

[30] The fraction explained by *BIDASK* is significantly negative because the adding-up constraint in stage four requires *BIDASK* and the residual component to add up to the stage one *PROD* slope. *BIDASK* positively predicts returns and it is also positively correlated with *PROD* after controlling for other competing variables. As a result, *BIDASK* does not explain the negative relation between firm productivity and future returns. Therefore, the contribution of *BIDASK* to explaining the firm productivity effect is negative.

[31] In unreported robustness checks, we use (i) raw returns or (ii) adjusted stock returns – the residual from the monthly cross-sectional regression of raw stock returns on *ME*, *B/M*, *12MPRET* and past one-month return – as the dependent variable. The results are qualitatively similar. We also include proxies for distress risk as candidate variables in our decomposition tests. They only explain at most 10% of the firm productivity effect.

Acknowledgments

This project was completed in part while Ang was completing his doctoral dissertation at the University of Melbourne. We are grateful to the editor (Kewei Hou), the anonymous associate editor, the anonymous referee, Andrew Ainsworth, Hang Bai (CICF discussant), Stephen Brown, Zhanhui Chen, Tarun Chordia, Doug Foster, Ferdinand Gul, Roy Kouwenberg, Alok Kumar, Roger Loh, Ben Marshall (SIRCA discussant), Byoung-Kyu Min, Buhui Qiu, Avanidhar Subrahmanyam, Takeshi Yamada, Martin Young (AsFA discussant), Qi Zeng, and the seminar participants at the Chinese International Conference in Finance (CICF), Asian Finance Association (AsFA) Conference, SIRCA Young Researcher Workshop, Deakin University, Mahidol University, University of Adelaide and University of Sydney for their helpful comments and suggestions. We thank Tarun Chordia, Ken French, Selale Tuzel, and Jeffrey Wurgler for providing data. This paper was previously circulated as 'Understanding the Firm-Productivity Effect in Stock Returns' and 'A Multidimensional Understanding of the Firm-Productivity Effect'. The views expressed in this paper are those of the authors, and do not necessarily reflect those of the Hong Kong Monetary Authority, Hong Kong Academy of Finance, Hong Kong Institute for Monetary and Financial Research, its Council of Advisers, or the Board of Directors. All errors are our own.

Appendix A

3Y ΔPROD:	Average of annual change in the percentile of firm productivity score over the past three year. Data source: CRSP and Compustat.
3Y ΔROA:	Average of the three latest year-to-year change in operating performance measured by return on 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.
BIDASK	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.
B/M:	Book-to-market equity ratio, calculated as book value of equity at the end of fiscal year t divided by market equity at the end of calendar year t. Book equity is total assets (item AT) 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. Market equity is closing share price times number of shares outstanding. Data source: Compustat and CRSP.
DD:	Merton (1974) Distance-to-default, constructed as in Vassalou and Xing (2004). Data source: Compustat and CRSP.
DVOL:	Daily dollar trading volume, which is closing share price times the trading day's share trading volume, averaged over the year at the end of June of calendar year t + 1. Data source: CRSP.
GP/A:	Gross profitability, measured as gross profit (item GP) for fiscal year t scaled by total assets (item AT) at the end of fiscal year t. Data source: Compustat.
GS:	Growth in sales, calculated as the average of the five latest year-to-year growth in revenue (item REVT). Data source: Compustat.
HIRING:	Employee growth, calculated as the change in the number of employees (item EMP) over fiscal year t scaled by the number of employees at the beginning of fiscal year t. Data source: Compustat.
I/K:	Investment-to-capital ratio, calculated as capital expenditures (item CAPX) for fiscal year t scaled by the beginning net book value of property, plant, and equipment (item PPENT) at the beginning of fiscal year t. Data source: Compustat.
IF:	Investment frictions, calculated as the average of percentile rankings of the inverse of firm age, total assets, and payout ratio. Data source: Compustat.
ILLIQ:	Amihud (2002) price impact, measured as the time-series average of absolute value of daily returns scaled by the trading day's dollar trading volume over the year at the end of June of calendar year t + 1. Data source: CRSP.
IVOL:	Idiosyncratic stock return volatility, which is the standard deviation of residuals from the time-series regression of daily stock returns as dependent variable and the Fama and French (1993) three factors as independent variables, estimated at the end of June of calendar year t + 1 using the latest month of returns. Data source: CRSP and Kenneth French Data Library.
LEV:	Leverage, measured as the ratio of long-term debt (item DLTT) to the sum of long-term debt and market equity at the end of fiscal year t. Data source: Compustat and CRSP.
ME:	Market equity, calculated as closing share price times number of shares outstanding at the end of June of calendar year t + 1. Data source: CRSP.
MISP:	A relative mispricing measure constructed from 10 percentiles of 10 firm characteristics that are well known in predicting stock returns. Data source: Compustat and CRSP.

OC: Operating costs, calculated as the sum of cost of goods sold and selling, general and administrative expense for fiscal year t, scaled by total assets at the beginning of fiscal year t. Data source: Compustat.

O-score: Ohlson (1980) bankruptcy score, is calculated as

$$\begin{aligned}\text{O-score} = & -4.07 \times \ln(\text{A}) + 6.03 \times (\text{L/A}) - 1.43 \times (\text{CA} - \text{CL})/\text{A} + 0.0757 \times \text{CL/CA} \\ & -2.37 \times \text{NI/A} + 0.285 \times \text{Loss} - 1.72 \times \text{NegBook} - 0.521 \times \Delta\text{NI} \\ & -1.83 \times \text{Op/L},\end{aligned}$$

where ln(A) is the logarithm of total assets (item AT), L is total liabilities (item LT), A is total assets (item AT), CA is current assets (item ACT), and CL is current liabilities (item LCT) at the end of fiscal year t. NI is net income (item NI) for fiscal year t. Loss is equal to one if net income (item NI) for fiscal year t and net income (item NI) for fiscal year t-1 are negative and zero otherwise. NegBook is equal to one if L is greater than A and zero otherwise. ΔNI is change in net income (item NI) from fiscal year t-1 to fiscal year t, scaled by the sum of the absolute values of the net income (item NI) over 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 fiscal year t, which is depreciation expenses (item DP) multiplied by market equity and divided by total assets (item AT) minus book value of equity plus market equity at the end of fiscal year t. Book equity is total assets (item AT) 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. Market equity is closing share price times number of shares outstanding. Data source: Compustat and CRSP.

P1MRET: Previous one-month stock return. Data source: CRSP.

P6MRET: Past six-month stock returns from the end of December calendar year t to the end of May of calendar year t + 1. Data source: CRSP.

P3YRET: Previous three-year stock return. Data source: CRSP.

PROD: Firm productivity score, estimated using Eqs. (1) and (2). Data source: Compustat and CRSP.

P/CF: Price to cash flow ratio, measured as stock price at the end of June year t divided by cash flow at the end of fiscal year t. Data source: Compustat and 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.

TAG: Total asset growth, calculated as total assets (item AT) at the end of fiscal year t minus total assets at the end of fiscal year t-1, scaled by total assets at the end of fiscal year t-1. Data source: Compustat.

TFP: Total factor productivity. Data source: İmrohoroğlu and Tüzel (2014).

Z-score: Altman (1968) Z-score, is calculated as

$$\begin{aligned}\text{Z-score} = & -1.2 \times (\text{CA} - \text{CL})/\text{A} - 1.4 \times \text{RE/A} - 3.3 \times \text{EBIT/A} - 0.60 \times \text{MV/L} \\ & -0.999 \times \text{S/A},\end{aligned}$$

where CA is current assets (item ACT), CL is current liabilities (item LCT), A is total assets (item AT), and L is total liabilities (item LT) at the end of fiscal year t. RE is retained earnings (item RE), EBIT is earnings before interest and taxes (item REVT minus item COGS minus item XSGA), and S is sales revenue (item REVT) for fiscal year t. MV is market equity at the end of year t. Data source: Compustat and CRSP.

β: Capital asset pricing model (CAPM) beta, which is the slope of the time-series regression of monthly stock return in excess of the risk-free rate as dependent variable and the monthly market premium as independent variable, estimated at the end of June of calendar year *t* with a full history of 36 months of observations. Data source: CRSP and Kenneth French Data Library.

Appendix B. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jempfin.2020.05.008.

References

Aigner, Dennis, Knox Lovell, C.A., Schmidt, Peter, 1977. Formulation and estimation of stochastic frontier production function models. J. Econometrics 6, 21–37.
Ali, Ashiq, Hwang, Lee-Seok, Trombley, Mark A., 2003. Arbitrage risk and the book-to-market anomaly. J. Financ. Econ. 69, 355–373.
Altman, Edward I., 1968. Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. J. Finance 23, 189–209.
Amihud, Yakov, 2002. Illiquidity and stock returns: cross-section and time-series effects. J. Financial Mark. 5, 31–56.
Ang, Andrew, Hodrick, Robert J., Xing, Yuhang, Zhang, Xiaoyan, 2006. The cross-section of volatility and expected returns. J. Finance 61, 259–299.
Avramov, Doron, Chordia, Tarun, Jostova, Gergana, Philipov, Alexander, 2013. Anomalies and financial distress. J. Financ. Econ. 108, 139–159.
Baker, Malcolm, Wurgler, Jeffrey, 2006. Investor sentiment and the cross-section of stock returns. J. Finance 61, 1645–1680.
Barberis, Nicholas, Greenwood, Robin, Jin, Lawrence, Shleifer, Andrei, 2015. X-capm: An extrapolative capital asset pricing model. J. Financ. Econ. 115, 1–24.
Barberis, Nicholas, Thaler, Richard, 2003. A survey of behavioral finance. In: Handbook of the Economics of Finance. pp. 1053–1128.
Belo, Frederico, Lin, Xiaoji, Bazdresch, Santiago, 2014. Labor hiring, investment, and stock return predictability in the cross section. J. Political Econ. 122, 129–177.

Carhart, M., 1997. On persistence in mutual fund performance. J. Finance 52, 57–82.
Cochrane, John H., 1991. Production-based asset pricing and the link between stock returns and economic fluctuations. J. Finance 46, 209–237.
Cochrane, John H., 1996. A cross-sectional test of an investment-based asset pricing model. J. Political Econ. 104, 572–621.
Cohen, Lauren, Diether, Karl, Malloy, Christopher, 2013. Misvaluing innovation. Rev. Financ. Stud. 26, 635–666.
Cohen, Lauren, Frazzini, Andrea, 2008. Economic links and predictable returns. J. Finance 63, 1977–2011.
Cohen, Lauren, Lou, Dong, 2012. Complicated firms. J. Financ. Econ. 104, 383–400.
Daniel, Kent, Grinblatt, Mark, Titman, Sheridan, Wermers, Russ, 1997. Measuring mutual fund performance with characteristic-based benchmarks. J. Finance 52, 1035–1058.
Daniel, Kent, Titman, Sheridan, 1997. Evidence on the characteristics of cross sectional variation in stock returns. J. Finance 52, 1–33.
Daniel, Kent, Titman, Sheridan, 2006. Market reactions to tangible and intangible information. J. Finance 61, 1605–1643.
De Bondt, Werner F.M., 1993. Betting on trends: Intuitive forecasts of financial risk and return. Int. J. Forecast. 9, 355–371.
De Bondt, Werner F.M., Thaler, Richard, 1985. Does the stock market overreact? J. Finance 40, 793–805.
De Long, J. Bradford, Shleifer, Andrei, Summers, Lawrence H., Waldmann, Robert J., 1990. Noise trader risk in financial markets. J. Political Econ. 98, 703–738.
Fama, Eugene F., French, Kenneth R., 1993. Common risk factors in the returns on stocks and bonds. J. Financ. Econ. 33, 3–56.
Fama, Eugene F., French, Kenneth R., 1997. Industry costs of equity. J. Financ. Econ. 43, 153–193.
Fama, Eugene F., French, Kenneth R., 2015. A five-factor asset pricing model. J. Financ. Econ. 116, 1–22.
Fama, Eugene F., MacBeth, James D., 1973. Risk, return, and equilibrium: Empirical tests. J. Political Econ. 81, 607–636.
Fitzgerald, Tristan, Balsmeier, Benjamin, Fleming, Lee, Manso, Gustavo, 2019. Innovation search strategy and predictable returns. Manage. Sci. forthcoming.
Franzen, Laurel A., Rodgers, Kimberly J., Simin, Timothy T., 2007. Measuring distress risk: The effect of R & D intensity. J. Finance 62, 2931–2967.
Frazzini, Andrea, Lamont, Owen A., 2008. Dumb money: Mutual fund flows and the cross-section of stock returns. J. Financ. Econ. 88, 299–322.
Greenwood, Robin M., Shleifer, Andrei, 2014. Expectations of returns and expected returns. Rev. Financ. Stud. 27, 714–746.
Griffin, John M., Lemmon, Michael L., 2002. Book–to–market equity, distress risk, and stock returns. J. Finance 57, 2317–2336.
Habib, Michel A., Ljungqvist, Alexander, 2005. Firm value and managerial incentives: A stochastic frontier approach. J. Bus. 78, 2053–2093.
Hirshleifer, David, 2001. Investor psychology and asset pricing. J. Finance 56, 1533–1597.
Hirshleifer, David, Hsu, Po-Hsuan, Li, Dongmei, 2013. Innovative efficiency and stock returns. J. Financ. Econ. 107, 632–654.
Hirshleifer, David, Li, Jun, Yu, Jianfeng, 2015. Asset pricing in production economies with extrapolative expectations. J. Monetary Econ. 76, 87–106.
Hou, Kewei, Loh, Roger K., 2016. Have we solved the idiosyncratic volatility puzzle? J. Financ. Econ. 121, 167–194.
Hou, Kewei, Xue, Chen, Zhang, Lu, 2015. Digesting anomalies: An investment approach. Rev. Financ. Stud. 28, 650–705.
Hsu, Po-Hsuan, 2009. Technological innovations and aggregate risk premiums. J. Financ. Econ. 94, 264–279.
İmrohoroğlu, Ayşe, Tüzel, Şelale, 2014. Firm-level productivity, risk, and return. Manage. Sci. 60, 2073–2090.
Jones, Christopher S., Tuzel, Selale, 2013. Inventory investment and the cost of capital. J. Financ. Econ. 107, 557–579.
Kahneman, D., Slovic, P., Tversky, A., 1982. Judgment under Uncertainty: Heuristics and Biases. Cambridge University Press, New York.
La Porta, Rafael, Lakonishok, Josef, Shleifer, Andrei, Vishny, Robert, 1997. Good news for value stocks: Further evidence on market efficiency. J. Finance 52, 859–874.
Lakonishok, Josef, Shleifer, Andrei, Vishny, Robert W., 1994. Contrarian investment, extrapolation, and risk. J. Finance 49, 1541–1578.
Lam, F.Y. Eric C., John Wei, K.C., 2011. Limits-to-arbitrage, investment frictions, and the asset growth anomaly. J. Financ. Econ. 102, 127–149.
Li, Erica X.N., Livdan, Dmitry, Zhang, Lu, 2009. Anomalies. Rev. Financ. Stud. 22, 4301–4334.
Li, Dongmei, Zhang, Lu, 2010. Does q-theory with investment frictions explain anomalies in the cross section of returns? J. Financ. Econ. 98, 297–314.
Lipson, Marc L., Mortal, Sandra, Schill, Michael J., 2011. On the scope and drivers of the asset growth effect. J. Financ. Quant. Anal. 46, 1651–1682.
Liu, Laura X., Whited, Toni M., Zhang, Lu, 2009. Investment-based expected return. J. Political Econ. 117, 1105–1139.
Liu, Laura X., Zhang, Lu, 2014. A neoclassical interpretation of momentum. J. Monetary Econ. 67, 109–128.
Livdan, Dmitry, Sapriza, Horacio, Zhang, Lu, 2009. Financially constrained stock returns. J. Finance 64, 1827–1862.
Livnat, Josuha, Mendenhall, Richard R., 2006. Comparing the post-earnings announcement drift for surprises calculated from analyst and time series forecasts. J. Account. Res. 44, 177–205.
Lou, Dong, 2012. A flow-based explanation for return predictability. Rev. Financ. Stud. 25, 3457–3489.
McLean, R. David, 2010. Idiosyncratic risk, long-term reversal, and momentum. J. Financ. Quant. Anal. 45, 883–906.
Merton, Robert C., 1974. On the pricing of corporate debt: The risk structure of interest rates. J. Finance 29, 449–470.
Miller, Edward M., 1977. Risk, uncertainty, and divergence of opinion. J. Finance 32, 1151–1168.
Newey, Whitney K., West, Kenneth D., 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica 55, 703–708.
Nguyen, Giao X., Swanson, Peggy E., 2009. Firm characteristics, relative efficiency, and equity returns. J. Financ. Quant. Anal. 44, 213–236.
Novy-Marx, Robert, 2011. Operating leverage. Rev. Finance 15, 103–134.
Ohlson, James A., 1980. Financial ratios and the probabilistic prediction of bankruptcy. J. Account. Res. 18, 109–113.
Pontiff, Jeffrey, 1996. Costly arbitrage: Evidence from closed-end funds. Q. J. Econ. 111, 1135–1151.
Pontiff, Jeffrey, 2006. Costly arbitrage and the myth of idiosyncratic risk. J. Account. Econ. 42, 35–52.
Shen, Junyan, Yu, Jianfeng, Zhao, Shen, 2017. Investor sentiment and economic forces. J. Monetary Econ. 86, 1–21.
Shleifer, Andrei, Vishny, Robert W., 1997. The limits of arbitrage. J. Finance 52, 35–55.
Shumway, Tyler, 1997. The delisting bias in crsp data. J. Finance 52, 327–340.
Sirri, Erik R., Tufano, Peter, 1998. Costly search and mutual fund flows. J. Finance 53, 1589–1622.
Stambaugh, Robert F., Yu, Jianfeng, Yuan, Yu, 2012. The short of it: Investor sentiment and anomalies. J. Financ. Econ. 104, 288–302.
Stambaugh, Robert F., Yu, Jianfeng, Yuan, Yu, 2015. Arbitrage asymmetry and the idiosyncratic volatiliy puzzle. J. Finance 70, 1903–1948.
Vassalou, Maria, Xing, Yuhang, 2004. Default risk in equity returns. J. Finance 59, 831–868.
Zhang, Lu, 2005. The value premium. J. Finance 60, 67–103.