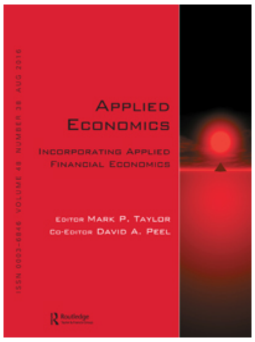

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Productivity growth and stock returns: firm- and aggregate-level analyses

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ABSTRACT
A firm's stock return is affected not only by its own productivity growth rate, but also by other firms' productivity growth rates. We show that this spillover effect is significant and time-varying, and underlies a fallacy of composition observed in late 20th century U.S. data: stock returns and productivity growth are correlated positively in firm-level data but negatively in aggregate data. This seeming fallacy of composition reflects Schumpeterian creative destruction: a few technology winners' stocks rise with their rising productivity while many technology losers' stocks fall with their declining productivity. Thus, most individual firms' stock returns correlate negatively with aggregate productivity growth. This implies that technological innovation need not be a blessing for all firms and as a result, for investors holding the market. Our findings also provide a firm-level technology innovation-based explanation of prior findings that the market return correlates negatively with aggregate earnings.

KEYWORDS
Technological innovation; stock return; heterogeneity; productivity; fallacy of composition

JEL CLASSIFICATION
G10; O33

> *The first rule of any technology used in a business is that automation applied to an efficient operation will magnify the efficiency. The second is that automation applied to an inefficient operation will magnify the inefficiency.*
>
> *Bill Gates*

I. Introduction

Although productivity growth (a measure related to economic profits and often associated with technological progress) is of central importance in economics, its importance in finance remains largely uncharted.[1] Estimated annual firm-level productivity growth rates for U.S. Compustat firms from 1970 to 2006 let us explore the contemporaneous relationships between firm-level and aggregate stock returns and firm-level and aggregate productivity growth rates.[2] This exercise supplements recent theoretical and empirical works revealing economically significant *negative spillovers* from technological innovation on established firms.

Endogenous growth theory emphasizes *positive spillovers* from innovation. Popular endogenous growth models (Romer 1990; Aghion and Howitt 1992) posit innovation creating wealth in two ways. First, an innovating firm invests in a new technology, creating wealth for its shareholders. Second, other firms throughout the economy adopt, imitate or improve the innovation, generating positive spillovers that create far more wealth for their shareholders. For example, AT&T's 1970s semiconductor innovations first spilled over into electronics parts firms, and then to other sectors, including autos, home appliances and retailing (Ruttan 2001). Bloom, Schankerman, and van Reenen (2013) find evidence of positive spillovers from research and development (R&D) to firms with similar technologies, as identified by patent citations.

However, other recent theoretical and empirical work associates the diffusion of a new technology across the economy with a widened performance gap, as increasingly productive technology winners leave increasingly troubled loser firms behind (Chun et al. 2008; Bena and Garlappi 2012). Tirole (1988) emphasizes these negative spillovers of innovation as driven mainly by product market rivalry or

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[1]*Economic profit* is total revenue less total costs. *Productivity growth* is growth in revenues less growth in total costs. *Accounting profit* or *earnings*, differs from *economic profit* in subtracting accounting (rather than economic) depreciation, and in not subtracting the cost of equity capital. *Economic profit* associated with technological progress is alternatively characterized as an *entrepreneurial rent* – that is, a return to creativity.

[2]We define aggregate variables as weighted averages of firm-level variables throughout.

competition. Hobijn and Jovanovic (2001) and Gârleanu, Kogan, and Panageas (2012) model broad-based technological progress inducing *displacement risk*, a negative spillovers of technological innovation; that is, an erosion in the values of established firms' physical (and human) capital. Kogan, Papanikolaou, and Stoffman (2015) develop a general equilibrium model in which the benefits of technological innovation are distributed asymmetrically, distinguishing winners from losers. These results recall Schumpeter's (1912) view of innovation as a process of *creative destruction*. Schumpeter begins with an innovating firm investing in new technology that boosts its economic profits, creating wealth for its own shareholders. But Schumpeter envisions shareholder wealth destruction at the innovators' competitor firms because they fail to utilize the new technology as productively. Consistent with the negative spillover effect, Megna and Klock (1993) document firms' share prices dropping markedly on news of a rival's innovation success in the semiconductor sector.

In this article, we measure the negative spillover effect of technological innovation at firm level for all the industries covered by Compustat and Center for Research in Security Prices (CRSP) data for a long period between 1970 and 2006.[3] We follow the growth theory literature in using firm-level total factor productivity (TFP) growth as a proxy for economically profitable technological innovation.[4] We follow the finance literature in using stock returns to measure changes in firms' market values.

Our findings are summarized as follows.

First, the typical firm's stock price rises significantly as its own TFP rises, but falls significantly as aggregate TFP rises, indicating negative spillovers. This implies that economy-wide technological innovation need not lift the valuations of all firms, and suggests Schumpeterian creative destruction: a few technology winners' stocks rise with their rising productivity while many technology losers' stocks fall with their declining productivity. This is observed in both the manufacturing and the service sectors.[5] We also find a significant improvement in goodness of fit (between 25% and 74%, depending on the specification) from including aggregate TFP growth in regression analysing the contemporaneous relationship between firm-level stock return and firm-level TFP growth. This is consistent with the importance of a negative spillover effect of technological innovation. Our result differs from Bloom, Schankerman, and van Reenen (2013), who find a positive spillover effect of R&D activity among firms citing each other's patents and who assume a homogenous spillover coefficient.[6] Our results extend theirs by defining innovation more broadly to include anything that boosts TFP, whether R&D-related or patentable or not, and by allowing for heterogeneous spillover coefficients across firms.

Second, while firm-level TFP growth and firm-level stock return are contemporaneously positively associated, aggregate TFP growth and aggregate stock return are contemporaneously negatively associated. This seeming contradiction is readily explicable because the economy-level correlation of TFP growth with the stock market's return is a weighted average of the heterogeneous, but mostly negative, correlations of individual firms' stock returns with aggregate TFP growth. The firm-level correlation, in contrast, reflects a consistently positive linkage between a firm's own TFP growth and its own stock's return. Creative destruction provides a complete explanation of all of these results. Also, the negative reaction of firm-level stock return to aggregate TFP growth is evident in most industries, suggesting that negative spillovers associated with creative destruction are not limited to certain high-tech sectors.

Third, the observed magnitude of this negative spillover effect exhibits substantial time-series variation: rising until 2000 and then gradually abating. This accords with the information technology (IT) boom of the 1990s inducing a wave of creative destruction across the U.S. economy that largely

[3]Our sample period ends in 2006, because the BEA and the BLS ceased reporting SIC-based industry-level deflators thereafter. The newly introduced NAICS-based industry classification was unavailable before 1987.
[4]See section 'Total factor productivity growth measure' for further discussion on the construction and interpretation of TFP.
[5]Creative destruction is induced by the frontier technology. In this article, we do not use a direct measure of the technology frontier. However, during the sample period of 1970–2006 in this article, several studies show that the aggregate TFP increased due to the advance in high TFP firms despite the increase in the dispersion of TFP among firms (Chun, Kim, and Morck 2011; Chun, Kim, and Lee 2015). This suggests that the advance in the technological frontier lead by winners is a key source of the aggregate TFP growth during the sample period.
[6]They gauge firm's technology proximity using patent citation-weighted R&D and associate a valuation premium with this measure. They conclude that positive spillovers raise the social return of R&D to twice its private return.

ran its course by the turn of the 20th century (Pástor and Veronesi 2009; Chun, Kim, and Morck 2011), possibly reflecting the time-varying displacement risk created by the differing stage of the IT diffusion.[7] In contrast, alternative explanations, such as a positive correlation between the discount rate and profit growth rate (Kothari, Lewellen, and Warner 2006; Hirshleifer, Hou, and Teoh 2009) or investors predicting aggregate earnings more accurately than firm-level earnings (Sadka and Sadka 2009), less readily account for this time variation. In particular, time-series variation in the spillover effect is well explained by the weighted average of the heterogeneous correlations of individual firms' stock returns with aggregate TFP growth. This shows that the changing relationship between the aggregate-level variables reflects firm-level heterogeneity associated with the effects of creative destruction, which is not clearly identifiable at the aggregate level.

Our findings imply that technological change widens inequality between firms, and the negative aggregate correlations we detect also suggest potentially widening inequality among shareholders. Much of the gain from successful innovation accrues to entrepreneur founders, venture capitalists or private equity investors who back innovative firms prior to their initial public offerings (IPOs; Gompers et al. 2008). Public investors who buy into IPOs tend to earn modest returns (Ritter and Welch 2002). Our result is consistent with these findings, in that public shareholders' wealth, represented by the market return, can decline as economy-wide innovations unfold. In this regard, our finding is also consistent with Ritter (2012) who argues that economic growth is not necessarily good news for diversified shareholders.[8] Finally, our findings supplement İmrohoroğlu and Tüzel (2014), who suggest aggregate productivity shocks as a systematic risk factor in stock returns. However, while they find heavier loadings on lower productivity firms only during recessions, our findings suggest that the displacement risk effect is also clearly observable cross-sectionally during the late 1990s' IT boom, in which the performance gap between technology winners and losers is widened.

This article is organized as follows. Section II describes the data. Section III reports empirical findings. Section IV discusses implications of our findings and Section V concludes.

II. Data

Total factor productivity growth measure

Firm-level TFP growth is measured annually because the necessary Compustat data are annual, and defined as

$$d\pi_{i,t} = dY_{i,t} - \frac{1}{2}[S_{L,i,t} + S_{L,i,t-1}]dL_{i,t} - \frac{1}{2}[S_{K,i,t} + S_{K,i,t-1}]dK_{i,t} \tag{1}$$

where $dY_{i,t}$, $dL_{i,t}$ and $dK_{i,t}$ are firm i's growth rates in value-added, labour and capital, respectively, and $S_{L,i,t}$ and $S_{K,i,t}$ are the share of the firm's costs payable to its providers of labour and capital, respectively.[9] The firm's costs of raw materials, electricity and other inputs to production are subtracted from its revenues each year to calculate its value-added, $Y_{i,t}$.

Real value-added is nominal value-added (*operating income before depreciation* [Compustat mnemonic: OIBDP] plus *labour and related expenses* [XLR or, if missing, an estimate described below]), all deflated by the Bureau of Economic Analysis (BEA) *gross product originating* (GPO) *value-added deflator* for firm i's two-digit primary industry, denoted $j(i)$. Before 1977, these deflators are unavailable, so we use *gross output and intermediate input prices* from the Bureau of Labor Statistics (BLS) multifactor productivity database to

[7]The negative correlation is not universally observed in other countries (Vivian and Jiang 2011) either, suggesting that the intensity of creative destruction might also differ across countries in a specific time period.

[8]Using cross-country data consisting of 19 developed countries between 1900 and 2011, Ritter (2012) reports a negative cross-country correlation between real per capita GDP growth and aggregate stock returns. Based on this, he posits that the technological innovation and its ensuing effects on competition, while increasing per capita GDP and consumer welfare, need not increase aggregate shareholder wealth.

[9]We follow Foster, Haltiwanger, and Syverson (2008), Aghion *et al*. (2009) and many other studies using the cost-share-based TFP index method for calculating TFP growth. This approach computes TFP growth directly, avoiding issues associated with various statistical estimation procedures. More importantly, Syverson (2011) shows this approach to be more reliable where production technologies are more flexible and heterogeneous. In contrast, the commonly used alternative approach based on production function estimation (Olley and Pakes 1996; Levinsohn and Petrin 2003), though useful in many settings, is highly problematic here because it assumes identical input trade-offs and returns to scale for all firms. The crucial importance of firm heterogeneity in this study thus necessitates the TFP index approach. Nonetheless, section 'Robustness checks' considers other methods of calculating TFP growth (Hall 1988; Basu and Fernald 1997) as robustness checks.

construct substitutes. Then, our *output growth rate* is $dY_{i,t} \equiv \ln(Y_{i,t}) - \ln(Y_{i,t-1})$.

The firm's labour cost share, $S_{L,i,t}$, is its *labour and related expenses* over this plus *capital services costs*. If *labour and related expenses* are unreported, we estimate them as *industry average wage* for $i(j)$, from GPO data, times the firm's *workforce* (EMP). If employees' benefits are excluded from *labour and related expenses* (XLR_FN), we estimate them using industry-level ratio of benefits to total compensation, from GPO data. *Capital services cost* is defined as *real capital stock, $K_{i,t}$,* times industry $j(i)$'s *rental price of capital*. To estimate the last, we use the BEA *fixed reproducible tangible wealth* data on the asset composition of each industry each year to aggregate BLS asset-specific rental prices of capital, tax-adjusted as in BLS (1997), using the Törnqvist method. Because DeAngelo and Roll (2015) report firm-level capital structures to be highly unstable, and driven by multi-year financing cycles, we do not attempt to adjust cost of capital for firm-level leverage. Firm *i*'s *capital cost share*, $S_{K,i,t}$, is one minus its *labour cost share*. We follow the BLS' method in smoothing $S_{L,i,t}$ and $S_{K,i,t}$ by averaging each across the current and previous years.

Discussion on other measures of technology innovation

Despite the supreme importance of TFP growth in the growth theory literature, its use in finance is nascent. Maksimovic and Phillips (2002) compare TFP in diversified firms versus conglomerates. Lieberman and Kang (2008) show the TFP variable to contain information above and beyond that discernible from earnings. Chun et al. (2008) link TFP variation to stock return volatility. İmrohoroğlu and Tüzel (2014) explore TFP shocks as a factor in a production-based asset pricing model.

Rather than using TFP as a measure of the economic profits associated with successful innovation, finance research tends to employ measures of innovative activity such as patents (Bena and Garlappi 2012; Kogan et al. 2012; Hirshleifer, Hsu, and Li 2013) or R&D (Chan, Lakonishok, and Sougiannis 2001; Hsu 2009; Lin 2012). Unfortunately, in the present context, well-known ambiguities limit the validity of inferences drawn from patent data (Nagaoka, Motohashi, and Goto 2010). First, a patent signifies that the firm believes it has intellectual property to protect, not that it has an economically successful innovation. Second, recent work shows that some 50% of patents are strategic – designed as tolls along rivals' possible research paths, pre-emptive moves to avoid litigation or cross-licensing, or defensive gambits to thwart rivals' research efforts (Hall and Ziedonis 2001; Bessen and Meurer 2008; Noel and Schankerman 2013).[10] Third, many economically important innovations are not patented because the innovator prefers alternative intellectual property defences – secrecy, complex design or speedy product development (Cohen, Nelson, and Walsh 2000).

R&D is a direct measure of the cost of inputs used in technological innovation, but also has limitations that render it problematic in this context. First, we are interested in the consequences of a firm's success as an innovator, not the innovation efforts of firms. Second, R&D spending disclosure is not mandatory unless the amounts are large, and is therefore a strategic decision – at least for small spenders. Third, disclosed R&D spending is highly concentrated in a few manufacturing sectors, such as computers and pharmaceuticals (Bloom, Schankerman, and van Reenen 2013). Fourth, R&D does not capture spending on non-scientific innovations in, for example, the service sector. While these limitations are bridgeable in other contexts, we require a measure of the ex-post gains due to successful innovation of any kind.

In this article, we wish to capture the effects of successful innovation of all types, not just innovation associated with scientific or engineering advances, which result from R&D spending and are patentable. Such forms of innovation include new managerial or organizational practices (Bloom, Sadun, and van Reenen 2012), learning by doing (Lucas 1988) and much innovation in the service and other non-manufacturing sectors which reflect non-negligible portion of productivity growth. TFP theoretically reflects not only R&D-financed and patentable innovation, but all forms of successful innovation. The cost of using TFP is that the

[10]To correct for these problems, some researchers use citation weights (e.g. Jaffe 1986; Bloom, Schankerman, and van Reenen 2013).

Table 1. Summary statistics, 1970–2006.

Panel A. Aggregate level

	Mean	SD	Min	Q1	Median	Q3	Max
Value weights							
Stock return	0.125	0.148	−0.153	0.043	0.117	0.222	0.426
TFP growth	0.008	0.067	−0.138	−0.042	0.014	0.046	0.110
Equal weights							
Stock return	0.174	0.222	−0.212	0.018	0.147	0.276	0.766
TFP growth	0.009	0.046	−0.105	−0.003	0.011	0.039	0.091

Panel B. Firm level

	Value weights		Equal weights						
	Mean	SD	Mean	SD	Min	Q1	Median	Q3	Max
Stock return	0.119	0.313	0.179	0.573	−0.978	−0.139	0.091	0.367	6.844
TFP growth	0.007	0.191	0.009	0.289	−6.216	−0.062	0.020	0.097	2.959

The sample sizes in Panels A and B are 37 and 42,032, respectively. Previous-year-end market capitalization is used as weights for both stock returns and TFP growth. The sample excludes firms with fiscal year-ends other than December and finance sector (SIC 6000–6999) firms.

variable is intrinsically noisy and can reflect luck, good or bad, as well as the fruits of broadly defined innovation. As long as these problems do not induce bias, they only work against our finding, reducing statistical significance.

Stock returns

When public shareholders learn that a firm risks losing business to more innovative or productive competitors, they bid down its share price. If successful adoption of new technology is substantially a winner-take-all competition, the vast majority of stocks should exhibit elevated displacement risk as technological progress accelerates, turning the relationship between aggregate-level TFP growth and stock returns predominantly negative if the associated productivity changes are at least partially unexpected by public shareholders at the beginning of the period, but understood by them at the end of the period after the firm's financial statements are made public. Further, due to the forward-looking nature of the stock market, stock price change could be more dramatic than underlying fundamentals (Mazzucato 2006).

To construct stock returns, we begin with all stocks covered by the CRSP from 1970 to 2006 for which matching TFP growth rates can be constructed. Following Kothari, Lewellen, and Warner (2006) and Hirshleifer, Hou, and Teoh (2009), we calculate annual total returns using monthly total returns from May of year t to April of year $t+1$. This 4-month lag mitigates problems associated with delays in Compustat annual data. We wish our annual returns to include all information released in the firm's financial statements for year t. As in Kothari, Lewellen, and Warner (2006) and Hirshleifer, Hou, and Teoh (2009), we drop all firms with fiscal year-ends other than December to permit a clean correspondence of calendar year stock return data with fiscal year accounting data.

Summary statistics are shown in Table 1. The aggregate variables are value-weighted and equally weighted averages of the firm-level variables. Value weighting is by prior year-end market capitalizations. Table 1 only includes firms with non-missing data for TFP growth and stock returns. The final sample consists of 42,032 firm-year observations from 1970 to 2006 encompassing all firms with December fiscal year-ends except those in the finance sector (SIC 6000–6999), whose financial data are not comparable. The value-weighted and equally weighted average firm-level stock returns are 12.5% and 17.4%, respectively. These closely approximate the average returns of the value-weighted (12.6%) and equally weighted (16.8%) CRSP market indexes.

III. Empirical results

Firm-level regressions

To explore the effect of technological innovation on realized stock returns, we estimate firm-level regressions of the form

$$\hat{r}_{i,t} \equiv r_{i,t} - E[r_{i,t}] = a_i d\pi_{i,t} + b_i d\pi_{m,t} + \varepsilon_{i,t} \qquad (2)$$

where firm i's realized abnormal stock return in year t, $\hat{r}_{i,t}$, equals the firm's observed total stock return,

$r_{i,t}$, minus its expected value, $E[r_{i,t}]$, estimated by CAPM (captial asset pricing model) or other factor models. TFP growth for individual firm i in year t and aggregate-level TFP growth are denoted $d\pi_{i,t}$ and $d\pi_{m,t}$, respectively, with the latter defined as the value-weighted average of the $d\pi_{i,t}$.[11] Our objective is to measure the correlation between firm i's abnormal stock return and changes in its economic profits, which we decompose into two components: the change in its economic profits associated with its own innovations, $d\pi_{i,t}$, and the change in its economic profits due to either positive or negative spillovers associated with the pace of economy-level innovation, as captured by $b_i d\pi_{m,t}$.

Because of the inclusion of $d\pi_{m,t}$ in Equation (2), the coefficient a_i on $d\pi_{i,t}$ captures the effect of firm i's firm-specific productivity growth on its own value.[12] The literature suggests that a_i should be positive. Chan, Martin, and Kensinger (1990) report significant positive stock price reactions when firms announce increased R&D budgets. Pakes (1985) and Blundell, Griffith, and van Reenen (1999) find higher shareholder value in firms with higher R&D or patents. İmrohoroğlu and Tüzel (2014) report a positive relationship between firms' stock returns and their contemporaneous TFP growth, which they interpret as exposure to a technology risk factor in an asset pricing framework.

The regression coefficient, b_i, measures the relationship of firm i's stock return to aggregate TFP growth, above and beyond that to firm i's own TFP growth. Thus, we assume that the effect of positive or negative spillovers on each firm's value is proportional to the change in aggregate economic profits, $d\pi_{m,t}$, but allow the ratio of proportionality to differ across firms. The existing literature has ambiguous predictions about b_i, the partial correlation of firm i's stock return with aggregate productivity growth. If positive spillovers predominate, firms' b_i should be largely positive, implying that most firms' stock market valuation rise as aggregate-level productivity rises; but if negative spillovers predominate, most firms' b_i should be negative, suggesting the negative spillover effect (Tirole 1988; Bena and Garlappi 2012; Gârleanu, Kogan, and Panageas 2012).

To operationalize Equation (2), we estimate the following regression separately for each firm using annual data windows of various lengths;

$$r_{i,t} - r_{f,t} = \alpha_i + a_i d\pi_{i,t} + b_i d\pi_{m,t} + \beta_i\left(r_{m,t} - r_{f,t}\right) + \varepsilon_{i,t}. \quad (3)$$

In Equation (3), firm i's expected return component is $r_{f,t} + \beta_i\left(r_{m,t} - r_{f,t}\right)$, estimated using the CAPM with the annualized 1-month treasury bill (T-bill) return, $r_{f,t}$, the CRSP value-weighted annual market return, $r_{m,t}$, and stock i's estimated CAPM beta, β_i.[13] The intercept, α_i, captures any remaining unexplained component in the firm's stock return.

Table 2 summarizes the distributional characteristics of the estimated a_i and b_i thus obtained. The first two columns describe coefficients from regressions using all available data for each of the 367 firms for which at least 20 observations exist over the sample period of 1970–2006. Numbers in parentheses are the number of firms with statistically significant (10%) coefficients. Using long-lived firms only allows more precise estimation of the coefficients in Equation (3), but eliminates firms founded after 1986 and thus obviously misses major innovative entrants during the 1990s IT boom. We, therefore, rerun Equation (3) for each firm using sequentially increasingly inclusive sampling criteria and shorter estimation windows. The third and the fourth columns use 30-year rolling windows and firms having 20 or more observations; the third pair of columns uses 20-year rolling windows and firms having 10 or more observations; the fourth pair of columns uses 10-year rolling windows and firms with five observations or more.[14]

[11]The aggregate TFP growth in Equation (2) excludes firm i to prevent spurious correlations between the TFP growth of firm i and the aggregate TFP growth.

[12]Including the lagged value of $d\pi_{m,t}$ in Equation (2) allows an AR(1) structure in the $d\pi_{m,t}$. This lets aggregate TFP growth obey an AR(1) process as well. Given this, b_i captures the explanatory power of 'unexpected' aggregate TFP growth on firm i's stock market return. We omit the lagged value as a robustness check and find the distributional characteristics of b_i to remain qualitatively similar to that described in the figures and tables.

[13]Our results are robust to alternative specifications. For example, to avoid any look-ahead bias, we instead use CAPM β_is estimated from the prior year's data to calculate the abnormal return in Equation (2), and then run regressions of that form. All the results remain qualitatively the same. Replicating this procedure using other asset pricing models to calculate the abnormal return in Equation (2) yields qualitatively similar results. See section 'Robustness checks' for details.

[14]There is one caveat with the restriction on the number of observations we use in estimating Equation (3). Jovanovic and Rousseau (2001) argue that a new technology may induce private firms to list sooner to utilize risk-tolerant equity financing. If new lists prosper on average after IPOs, we may interpret this as a positive spillover effect of technology innovation. If this is the case, we are underestimating the importance of the positive spillover effect since the restriction on the number of observations may exclude many of new lists. However, Fama and French (2004) report a lower survival rate for new lists in recent decades. This shows that not all the new entrants enjoy the positive spillover effects of technology innovations, suggesting that new lists also consist of extreme winners and extreme losers (Chun et al. 2008). This reduces the concern for underestimating the positive spillover effect by not including them. We thank an anonymous referee for pointing this out.

Table 2. Characteristics of coefficients on firm-level TFP growth, aggregate-level TFP growth and the market return in firm-level regressions explaining firm-level stock return.

Panel A. Coefficients on firm's own TFP growth (a_i)								
	2A.1		2A.2		2A.3		2A.4	
Number of coefficients								
Negative	94	(13)	678	(85)	3337	(333)	9899	(858)
Positive	273	(87)	1991	(573)	8978	(2253)	18,765	(3186)
Total	367	(100)	2669	(658)	12,315	(2586)	28,664	(4044)
Median	0.454	(1.066)	0.440	(1.257)	0.477	(1.546)	0.474	(1.871)
Mean (EW)	0.575	(1.223)	0.599	(1.329)	0.757	(1.852)	0.882	(2.207)
Mean (VW)	0.201	(0.362)	0.234	(0.221)	0.313	(0.298)	0.383	(1.017)
Panel B. Coefficients on aggregate TFP growth (b_i)								
	2B.1		2B.2		2B.3		2B.4	
Number of coefficients								
Negative	297	(96)	2139	(630)	8598	(1660)	18,000	(2278)
Positive	70	(5)	530	(24)	3717	(219)	10,664	(798)
Total	367	(101)	2669	(654)	12,315	(1879)	28,664	(3076)
Median	−0.974	(−1.998)	−0.902	(−2.167)	−0.815	(−2.738)	−0.797	(−3.237)
Mean (EW)	−0.955	(−2.105)	−0.979	(−2.402)	−0.831	(−2.553)	−0.730	(−2.132)
Mean (VW)	−0.437	(−1.211)	−0.411	(−1.616)	−0.400	(−1.600)	−0.295	(−1.335)
Panel C. CAPM beta (β_i)								
	2C.1		2C.2		2C.3		2C.4	
Number of coefficients								
Negative	54	(1)	506	(27)	3248	(114)	9052	(498)
Positive	313	(98)	2163	(587)	9067	(1590)	19,612	(2445)
Total	367	(99)	2669	(614)	12,315	(1704)	28,664	(2943)
Median	0.381	(0.762)	0.360	(0.767)	0.360	(1.040)	0.416	(1.345)
Mean (EW)	0.448	(0.842)	0.408	(0.820)	0.437	(1.096)	0.468	(1.165)
Mean (VW)	0.424	(0.656)	0.436	(0.701)	0.405	(0.858)	0.418	(1.091)

Panel D. Adjusted R^2				
	2D.1	2D.2	2D.3	2D.4
Median	0.082	0.072	0.057	0.068
Mean (EW)	0.106	0.097	0.082	0.069
Mean (VW)	0.109	0.095	0.096	0.081

Regression coefficients are estimated separately for each firm. The first pair of columns summarizes coefficients from regressions using all available data for each of the 367 firms with at least 20 observations in the sample window, 1970–2006. Numbers in parentheses are counts of firms with statistically significant (10%) coefficients. The second pair of columns uses 30-year rolling windows and includes firms with 20 or more in the window. The third pair of columns uses 20-year rolling windows and firms with 10 or more observations. The fourth pair of columns uses 10-year rolling windows and firms with five observations or more. Medians, equally weighted (EW) means and value-weighted (VW) means of coefficients are reported in the last three rows of each panel. The sample excludes firms with fiscal year-ends other than December and finance sector (SIC 6000–6999) firms.

First, consider the leftmost two columns, which summarize the coefficients for firm-level regression (Equation (3)) for firms having at least 20 annual observations. Column 2A.1 of Panel A reveals approximately 74% of the firm-level regression coefficients a_i to be positive. About 27% of the a_i coefficients are statistically significant at 10%, and 87% of these are positive. Column 2B.1 of Panel B summarizes the analogous distributional characteristics for the firm-level regression coefficients, b_i, which gauge the correlation of each firm's stock return with aggregate TFP growth. Some 81% of firms attract negative b_i coefficients. About 28% of the b_i are significant, and approximately 95% of these are negative. These results show that a firm's own stock return tends to correlate positively with its own innovation success, but negatively with the aggregate innovative success of the economy.[15]

The second three rows in each panel provide medians as well as equally weighted and value-weighted means of the estimated a_i and b_i regression coefficients. Again focusing on the first pair of columns, the equally weighted mean of the a_i is 0.575 and exceeds its value-weighted analogue of 0.201. The equally weighted mean of the b_i is −0.955, and likewise exceeds its value-weighted analogue of −0.437 in absolute value. These patterns in equally weighted versus value-weighted means suggest that smaller firms profit more from their own innovative successes, but also suffer worse ill effects amid aggregate innovative success.

[15]Estimating regression for each firm and counting significant coefficients fail to account for cross-firm correlations. An alternative approach, firm-level panel regressions assuming homogeneous a_i and b_i coefficients across firms and clustering by time, while imposing a different and more restrictive set of assumptions, reproduces the central findings reported in this section. See section 'Firm-level panel regressions' for details.

Column 2C.1 of Panel C of Table 2 shows the b_i and β_i coefficients to be very different too. About 85% of firm-level regressions attract positive β_i coefficients, indicating that firms' stock returns typically correlate positively with market returns. This also confirms that the market risk premium and aggregate TFP growth rate have different effects on stock returns. About 27% of the β_i are significant, and of these some 99% are positive. The equally weighted and value-weighted means of the β_i are similar: 0.448 and 0.424, respectively. The low means of the β_i reflect Compustat's more limited coverage of smaller firms and our requirement that firms to have a certain number of years of data, depending on the estimation window, removing younger firms from the sample.

The coefficients summarized in the first pair of columns arise from regressions using a single long window from 1970 to 2006 for each firm and using only firms having least 20 observations. This presumes constant regression coefficients over time for each individual firm. To let each firm's a_i and b_i vary over time, we rerun Equation (3) using alternative windows and inclusion criteria. The other columns in Table 2 summarize regression coefficients estimated using 30-year rolling windows with at least 20 observations, 20-year rolling windows with at least 10 observations and 10-year rolling windows with at least 5 observations.[16] Decreasing the size of the estimation window, while increasing the number of firms we can use, decreases the number of observations in each window used in estimating Equation (3) for each firm, reducing the fraction of coefficients attaining significance. Nonetheless, the basic pattern of predominantly positive a_i and predominantly negative b_i persists throughout the table. For example, column 2B.2 of Panel B, summarizing the b_i coefficients for 30-year rolling windows with at least 20 observations, shows approximately 80% of the b_i coefficients negative. About 25% of these are flagged for statistical significance and about 96% of these are negative. Column 2B.3 of Panel B, describing coefficients estimated in 20-year rolling windows with at least 10 observations, shows approximately 70% of the b_i coefficients negative. About 15% of these are flagged for statistical significance, and among these, some 88% are negative. Lastly, column 2B.4 of Panel B describes results from 10-year rolling windows with at least five observations. It shows approximately 63% of the b_i coefficients to be negative. About 11% of them are flagged as statistically significant and about 74% of these are negative. Thus, the 10-year windows entirely obviate statistical significance: 11% (3076 of 28,664 coefficients) – essentially the expected 10% incidence of Type II errors – are flagged for significance at 10%. However, Type II errors should be 50%, not 74%, negative, leaving even these runs suggestive of negative spillovers.

Panels A and B of Figure 1 graph the distribution of the firm-level regression a_i and b_i coefficients, respectively, estimated using 10-year rolling windows.[17] Panels A1 and B1 include all estimated coefficients, while Panels A2 and B2 include only coefficients that are significant at 10% or better. The distributions of the a_i and b_i differ starkly, and a significantly larger negative mass in the b_i distribution is apparent.

If b_i captures negative spillovers from aggregate productivity growth, the distribution characteristics of the b_i should vary over time as aggregate productivity growth accelerates and slows. Schumpeter (1939) posits that, as a major innovation first spreads across the economy, successful innovators far outpace each affected industry's increasingly troubled incumbents; but that once the innovation has propagated fully, and its best uses in each industry become apparent, an increasingly homogeneous set of surviving firms should compete increasingly on price, rather than new product or process development, causing profit rates should decline towards relatively low and homogenous levels. This thesis suggests a period of widening performance gaps as a new technology spreads followed by a period of narrowing performance gaps as it grows mature. Chun, Kim, and Morck (2011) show firm-performance heterogeneity among U.S. firms increasing until the end of the 20th century, but decreasing thereafter, and link this more

[16]Rolling windows induce serial correlation in firm's estimated coefficients in addition to the cross-firm correlations within windows (previous footnote). An alternative approach, panel regressions (section 'Firm-level panel regressions'), is more restrictive in assuming homogeneous a_i and b_i coefficients across firms and windows, but allows two-dimensional clustering (Thompson 2011) to reflect both cross-firm and time-series non-independence. This exercise confirms the findings in this section.

[17]We obtain similar figures for other estimation windows as well.

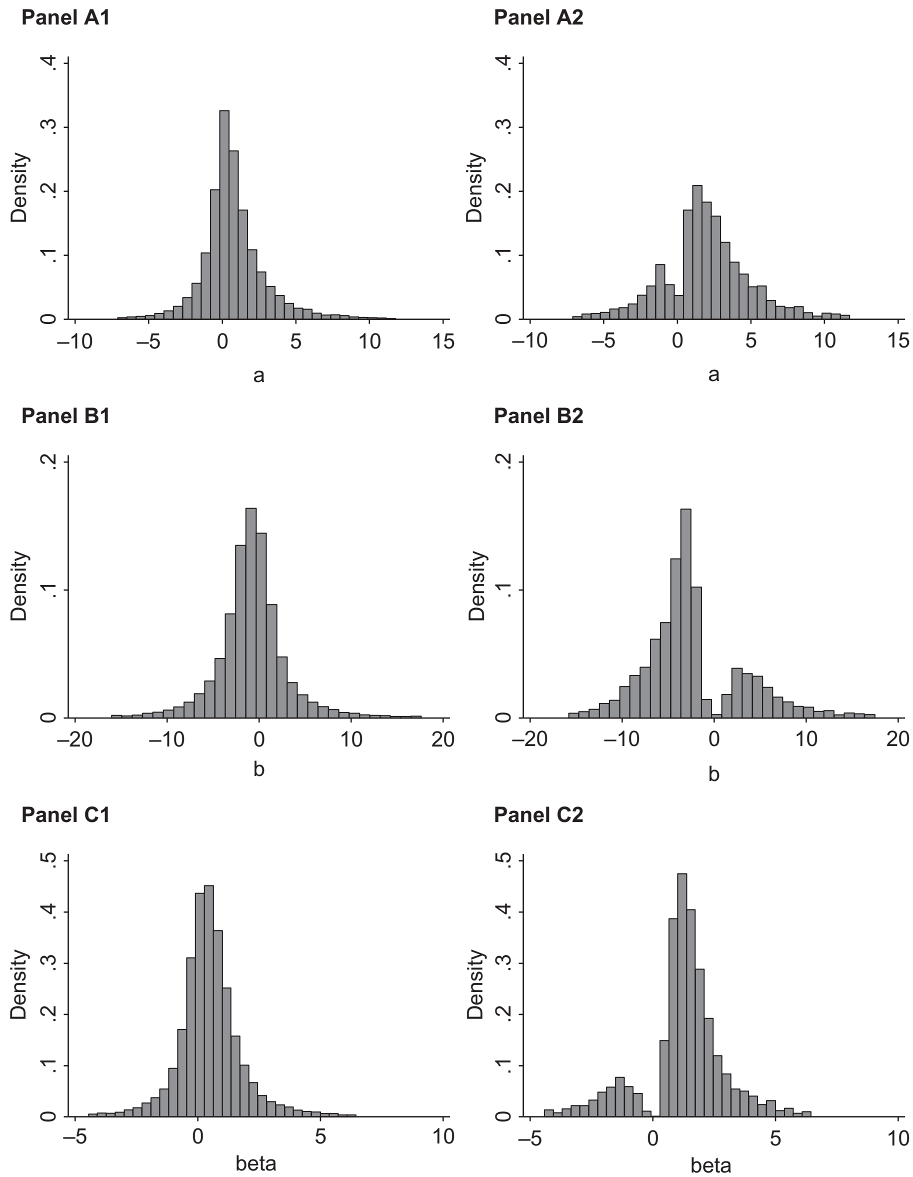

Figure 1. Distributions of firms' stock return responses to own and aggregate TFP growth: Panel A1. Firm-level TFP: all firms; Panel A2. Firm-level TFP: significant at 10%; Panel B1. Aggregate TFP: all firms; Panel B2. Aggregate TFP: significant at 10%; Panel C1. CAPM beta: all firms; Panel C2. CAPM beta: significant at 10%.
Figures omit top and bottom 1% of estimated coefficients.

precisely to the observed patterns of IT propagation in different industries. Pástor and Veronesi (2009) likewise interpret changing stock return volatility to conclude that the diffusion of IT was essentially complete in the United States by about 2002. Kogan et al. (2012) show that firms affected negatively by other firms' patents in the short run, generally eventually benefit from them in the long run – if they survive the initial negative shock. These considerations suggest specific patterns of time-series variation in the distribution characteristics of the b_i, for which we can test.

Panels A and B of Figure 2 summarize how distribution characteristics of the a_i and b_i change over time by plotting their decile cut-offs over successive 10-year rolling windows, each ending in the indicated year. The rightmost graphs in each panel plot differences between the distributions' 9th and 1st decile cut-offs.

Panel A of Figure 2 shows that, consistent with Table 2, the positive masses of the a_i greatly outweigh their negative masses throughout. Moreover, while their distributions narrow somewhat in the 1990s, their medians remain positive throughout. In contrast, the distributional characteristics of the

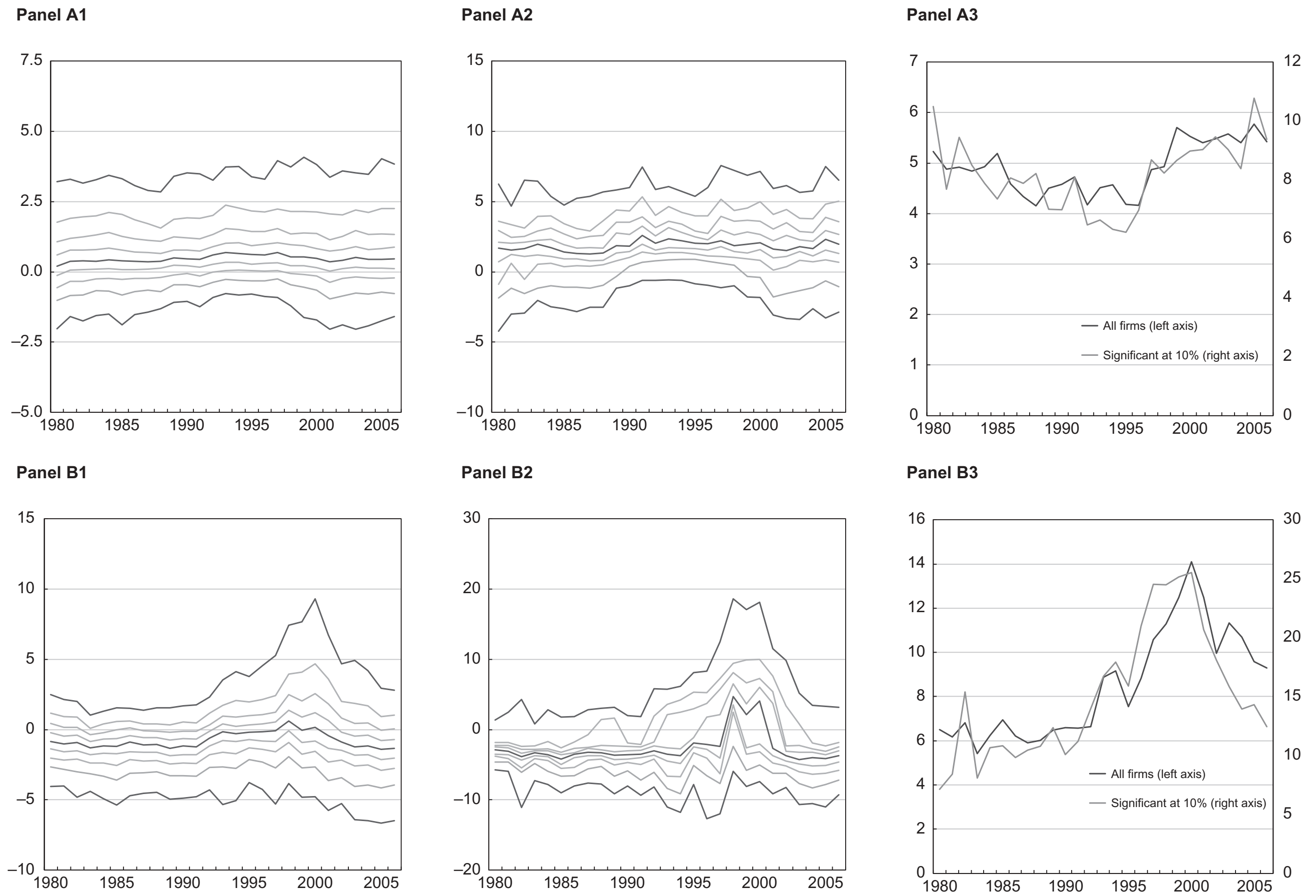

Figure 2. Dispersion in firm-level stock return responses to own and aggregate TFP growth: Panel A1. Firm-level TFP: all firms; Panel A2. Firm-level TFP: Significant at 10%; Panel A3. Firm-level TFP: 90 percentile minus 10 percentile; Panel B1. Aggregate TFP: all firms; Panel B2. Aggregate TFP: Significant at 10%; Panel B3. Aggregate TFP: 90 percentile minus 10 percentile.

Figures show distributions of decile cut-offs for coefficients on firm and aggregate TFP growth obtained from Equation (3) that are estimated over 10-year windows for each firm. In Panels A1, A2, B1 and B2, the three black lines, from the bottom up, track 10th, 50th (median) and 90th percentiles, respectively, by the end-year of each 10-year estimation window. Grey lines represent intermediate deciles. Panels A1 and B1 include all firms and Panels A2 and B2 include only firms with coefficients significant at 10%.

b_i change markedly with time. Panel B of Figure 2 shows that the median b_i remains negative, except in windows ending near the turn of the century, when the distribution of significant coefficients (Panel B2) both shifts its median into the positive range and distends its positive tail before reverting to its earlier form in later windows.

Panel A3 of Figure 2 shows the difference between 9th and 1st decile cut-offs of the a_i to be relatively stable throughout the sample period. Again, this contrasts starkly with the distributions of the b_i. Panel B3 of Figure 2 shows the difference between 9th and 1st decile cut-offs of the b_i increasing until the end of the 20th century, and then decreasing. The increasingly positive median of firm's b_i might reflect positive spillovers slowly overtaking negative spillovers as the new IT ran its course, but might also reflect generally upward biased stock returns as the 1990s dot.com bubble expanded. Regardless, most of the 1990s show predominantly negative b_i and the entire decade, even during the bubble period, exhibits a widening performance gap between sharply divided winners and losers as IT-related innovation peaked (Jovanovic and Rousseau 2005).

Figure 3 reports the empirical probability functions of firms' b_i, averaged across 1980–2006, by industry. The complete distributions of the b_i exhibit negative medians in 42 of 44 industries, and the distributions of the significant b_i (not shown) are likewise negative in 38 of 43 industries.[18] Figure 3

[18]One sector lacks significant coefficients.

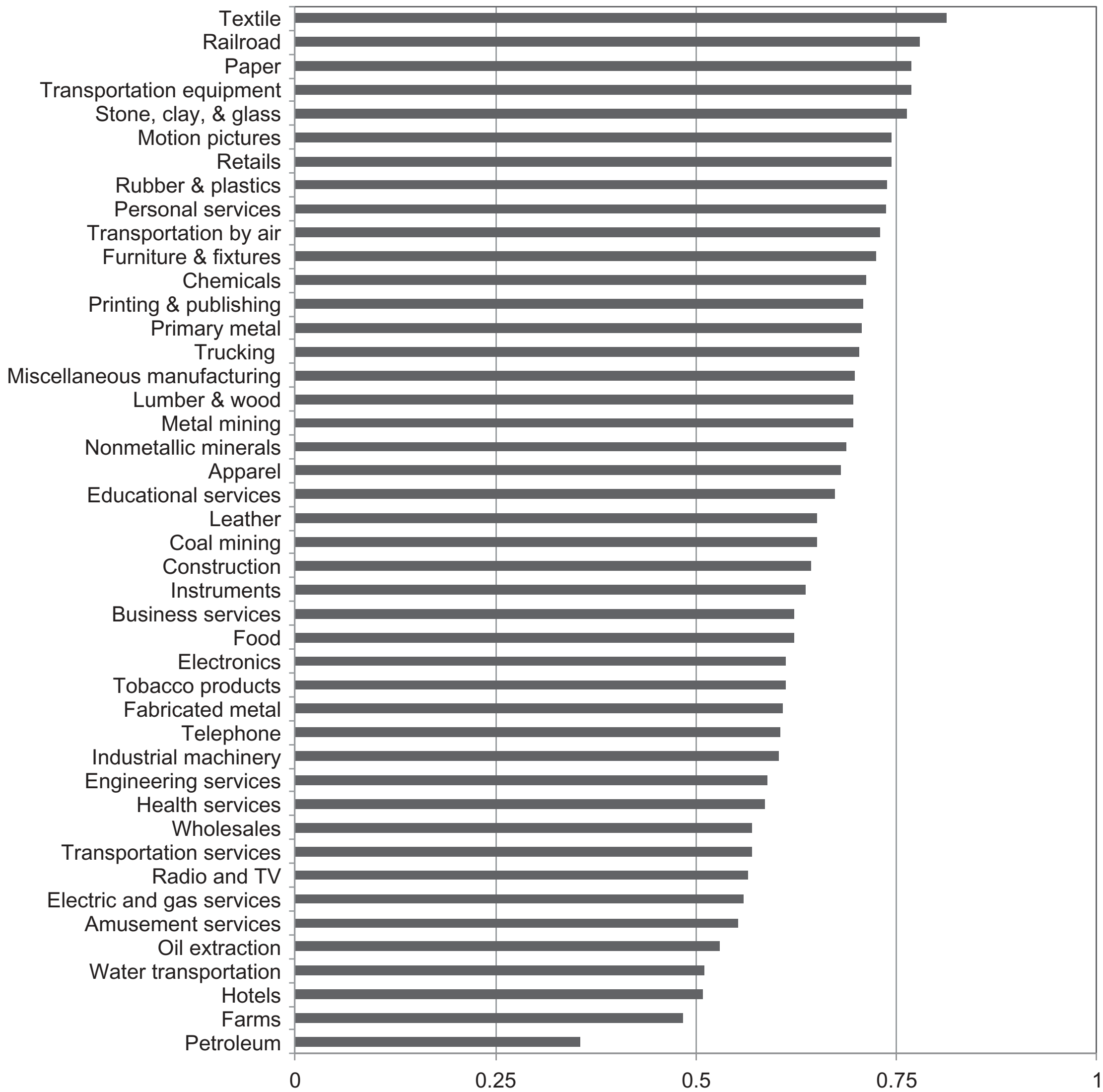

Figure 3. Fraction of firms with negative stock return response to value-weighted aggregate TFP growth, means over 1980–2006 by industry.

Each bar indicates the proportion of firms with negative stock return responses to aggregate TFP growth in Equation (3), averaged over the sample period of 1980–2006. The sample includes all industries with three or more firms in 1980–2006.

shows that the negative coefficients of b_i in Figure 2 are not concentrated within a few industries, but are characteristic of firms spread across the economy as a whole. Repeating this exercise, but separating manufacturing from non-manufacturing firms, yields similar patterns (not shown) revealing the pattern to be common across both broad sectors.

The findings in this section are consistent with stock returns reflecting Schumpeter's (1912) creative destruction. The thick positive tail of the a_i distribution reflects profits from firms' own innovations boosting their own share prices. The thin positive tail of the b_i distribution is consistent with a few 'winners' benefiting hugely from aggregate productivity growth, while the thicker negative tail is consistent with most firms being left behind by technological progress.

Aggregate-level regressions

To explore the relationship between the stock market return reacts and aggregate productivity growth, we regress the stock market return on aggregate TFP growth.

$$r_{m,t} = a + bd\pi_{m,t} + \varepsilon_{m,t}. \tag{4}$$

Table 3. Regressions of stock returns on TFP growth: aggregate-level versus firm-level panel regressions, 1970–2006.

Panel A. Aggregate level

	3A.1	3A.2	3A.3	3A.4
VW aggregate TFP	−0.622*	−0.649*		
	(0.359)	(0.357)		
Lagged VW aggregate TFP		0.462		
		(0.358)		
EW aggregate TFP			−1.385*	−1.557*
			(0.772)	(0.802)
Lagged EW aggregate TFP				0.677
				(0.802)
Constant	0.129***	0.126***	0.186***	0.181***
	(0.024)	(0.024)	(0.036)	(0.037)
Sample size	37	37	37	37
Adj. R^2	0.079	0.122	0.084	0.103

Panel B. Firm level

	3B.1	3B.2	3B.3	3B.4	3B.5	3B.6
Firm TFP	0.289***	0.289***	0.291***	0.296***	0.253***	0.261***
	(0.026)	(0.025)	(0.026)	(0.027)	(0.025)	(0.025)
Lagged firm TFP		0.019		0.024		0.035
		(0.017)		(0.014)		(0.022)
VW aggregate TFP	−1.175***	−1.129***				
	(0.343)	(0.325)				
Lagged VW aggregate TFP		0.788**				
		(0.324)				
EW aggregate TFP			−1.657**	−1.872***		
			(0.697)	(0.620)		
Lagged EW aggregate TFP				1.113***		
				(0.358)		
CAPM factor	0.592***	0.606***	0.679***	0.701***	0.636***	0.636***
	(0.150)	(0.126)	(0.174)	(0.158)	(0.176)	(0.175)
Sample size	42,032	42,032	42,032	42,032	42,032	42,032
Adj. R^2	0.092	0.100	0.090	0.098	0.074	0.074

Dependent variables in Panel A are value-weighted (VW) aggregate stock returns (columns 3A.1 and 3A.2) or equally weighted (EW) aggregate stock returns (columns 3A.3 and 3A.4). The dependent variable in Panel B is firm-level stock returns. Panel regressions in Panel B include firm-fixed effects. The sample excludes firms with fiscal year-ends other than December and finance sector (SIC 6000–6999) firms. Numbers in parentheses are standard errors. Standard errors in Panel B are year-clustered.
*Significant at the 10% level.
**Significant at the 5% level.
***Significant at the 1% level.

This specification follows from summing the regressions (Equation (2)) across all firms, weighting each by w_i.[19] The coefficient b, which captures the linkage between the stock market return and aggregate TFP growth, is simply the weighted average of the b_i in Equation (2). Thus, if positive spillovers outweigh negative spillovers across firms, the weighted average $b \equiv \sum_i w_i b_i > 0$; but if the negative spillover effect predominates, $b < 0$.[20] Moreover, if the distributional characteristic of the firm-level b_i differs for different estimation windows, b can vary through time, and even flip signs.

Panel A in Table 3 summarizes these regressions of (aggregate) stock market returns, $r_{m,t}$, on aggregate TFP growth, $d\pi_{m,t}$, taking aggregates as means of firm-level stock returns and TFP growth rates, respectively. The table displays regressions using value-weighted as well as equally weighted means. Firm-level stock returns are always measured from May of year t to April of year $t + 1$.

Regressions 3A.1 and 3A.2 show $d\pi_{m,t}$ defined here as the value-weighted mean TFP growth rate, attracting a significantly negative coefficient. Regression 3A.2 shows that including lagged TFP

[19]Summing both sides of Equation (2), weighting by w_i = firm i's prior year-end market capitalization, yields $\sum w_i \hat{r}_i \equiv r_{m,t} - E[r_{m,t}] = \sum_i w_i a_i d\pi_{i,t} + d\pi_{m,t} \sum_i w_i b_i$. This leads to Equation (4) only if $a \equiv E[r_{m,t}] + \sum_i w_i a_i d\pi_{i,t}$ is a constant within each sample period. This would follow if both $E[r_{m,t}]$ and $\sum_i w_i a_i d\pi_{i,t}$ were constant. Empirically, $E[r_{m,t}]$ need not be constant (Campbell, Lo, and MacKinlay 1997) and $\sum_i w_i a_i d\pi_{i,t}$ need not be zero – although $E[d\pi_{i,t}]$ is fairly close to zero (between 0.7% and 0.9% in Table 1). Nonetheless, if there is little time variation in $\sum_i w_i b_i$ within estimation windows, Equation (4) serves as a parsimonious specification. A comparison of point estimates, shown below, reveals that $b \cong \sum_i w_i b_i$ in corresponding estimation window, validating the assumption of a constant a in each window.

[20]If a few very large firms had $b_i > 0$, a positive b might ensue despite most firms having $b_i < 0$. However, equally weighted and value-weighted means of the b_i exhibit similar behaviour (see especially Figure 4).

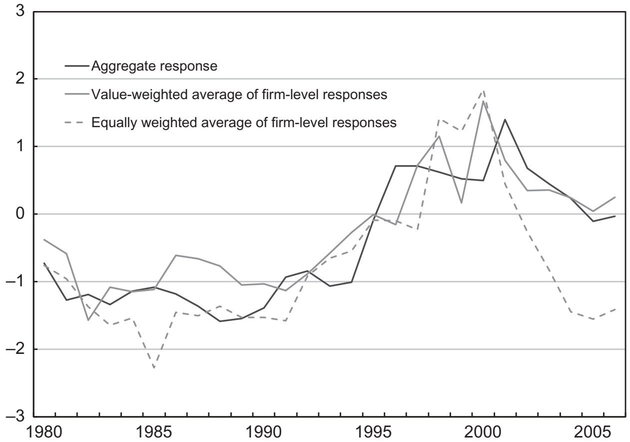

Figure 4. Aggregate-level versus mean firm-level stock return responses to aggregate TFP growth in rolling 10-year windows ending in the year indicated.

A black line is aggregate response coefficients obtained from Equation (4) over 10-year rolling windows. Grey and dotted lines are value-weighted and equally weighted averages of firm-level responses, respectively, obtained from firm-level regressions in Equation (3) that are estimated over 10-year windows for each firm.

growth as a control leaves this result qualitatively unchanged.[21] Regressions 3A.3 and 3A.4 repeat these exercises, but define $d\pi_{m,t}$ as an equally weighted mean TFP growth rate. The point estimates for b remain negative and significant, and roughly double in magnitude. Table 3 thus suggests that negative spillovers outweigh positive spillovers in the aggregate for the firms in our sample.

To explore the stability of b over time, Figure 4 plots estimates of the b coefficient from Equation (4) over successive 10-year rolling windows against the windows' end-years. The figure also plots the value-weighted and equally weighted means of the firm-level coefficients b_i from regressions (Equation (3)) estimated using the same rolling windows. These two series of means closely follow the aggregate-level regression coefficients b, though the equally weighted mean of the firm-level coefficients b_i is generally more negative than its value-weighted analogue, especially for windows ending after 2000. These patterns suggest that the time variation in b might be associated with a varying preponderance of negative firm-level coefficients b_i estimated using different windows.

Firm-level panel regressions

The previous sections show that firm-level stock returns are generally positively associated with firms' own productivity growth, but generally negatively associated with aggregate TFP growth. That is, in Equation (3), the a_i are generally positive and the b_i are generally negative. Moreover, the aggregate productivity growth coefficient b in Equation (4) closely tracks the means of the firm-level coefficients on aggregate productivity growth, b_i, in Equation (2), operationalized as Equation (3). These patterns suggest the alternative specification of panel regressions of the form

$$r_{i,t} = \sum_i \delta_i + ad\pi_{i,t} + bd\pi_{m,t} + \varepsilon_{i,t} \tag{5}$$

with $r_{i,t}$ and $d\pi_{i,t}$ the stock return and TFP growth rate, respectively, of firm i in year t, and with δ_i representing firm-fixed effects. Including aggregate TFP growth, $d\pi_{m,t}$, in the regression precludes time-fixed effects.

The advantage of the firm-by-firm regressions in the previous section is that each firm has a distinct set of coefficients, a_i and b_i, for each firm and window,[22] allowing an analysis of their distributional characteristics. However, spillovers complicate assessment of the overall significance of the coefficients a_i and b_i across many firms by inducing cross-firm correlations within a given window and, as noted above, coefficients estimated using overlapping windows may not be independent. The panel specification (Equation (5)), though more restrictive in requiring the firm-level coefficients in Equation (3) to be identical across firms and across time ($a_i = a$ and $b_i = b$ for each i in the whole sample),[23] permits clustering by year (to allow for cross-firm statistical dependence) or by firm (to address persistence in data for each firm). Both these considerations weigh against finding statistical significance in Equation (5). Standard errors with firm clustering are smaller, thus generating higher t-statistics than those with year clustering, a typical characteristic of asset pricing data (Petersen 2009). Clustering by firm or by firm and year simultaneously (Thompson

[21]Here and throughout, we define *qualitatively unchanged* to mean an identical pattern of signs and significance and point estimates of roughly comparable magnitude. This specification lets aggregate TFP growth obey an AR(1) process, thereby letting b gauge the importance of plausibly 'unexpected' TFP growth in regressions explaining the stock market return.

[22]More precisely, we estimate a_i^τ and b_i^τ for each firm i and for each estimation window τ. For brevity, τ is suppressed in our notation.

[23]Kogan et al. (2012) run similar firm-level panel regressions to examine the negative spillover effect. Their aggregate innovation measure, an economic importance-weighted average of other firms' patents, attracts a significant negative coefficient, also consistent with the negative spillover effect.

Table 4. Alternative specification for firm-level regressions explaining firm-level stock return: excluding aggregate-level TFP growth.

Panel A. Coefficients on firm's own TFP growth (a_i)

	4A.1		4A.2		4A.3		4A.4	
Number of coefficients								
Negative	122	(17)	819	(99)	3635	(363)	10,126	(877)
Positive	245	(66)	1850	(430)	8680	(1962)	18,538	(3115)
Total	367	(83)	2669	(529)	12,315	(2325)	28,664	(3992)
Median	0.258	(0.881)	0.284	(1.067)	0.380	(1.469)	0.388	(1.731)
Mean (EW)	0.404	(1.048)	0.438	(1.152)	0.651	(1.739)	0.710	(2.051)
Mean (VW)	0.100	(0.203)	0.117	(0.148)	0.187	(0.217)	0.233	(0.427)

Panel B. CAPM beta (β_i)

	4B.1		4B.2		4B.3		4B.4	
Number of coefficients								
Negative	40	(1)	437	(19)	2860	(85)	8065	(387)
Positive	327	(105)	2232	(660)	9455	(1923)	20,599	(3063)
Total	367	(106)	2669	(679)	12,315	(2008)	28,664	(3450)
Median	0.406	(0.753)	0.401	(0.783)	0.425	(1.071)	0.495	(1.438)
Mean (EW)	0.485	(0.856)	0.455	(0.864)	0.510	(1.159)	0.639	(1.442)
Mean (VW)	0.447	(0.618)	0.459	(0.728)	0.450	(0.892)	0.520	(1.281)

Panel C. Adjusted R^2

	4C.1	4C.2	4C.3	4D.4
Median	0.047	0.040	0.025	0.016
Mean (EW)	0.071	0.067	0.060	0.057
Mean (VW)	0.088	0.080	0.075	0.077

Regression coefficients are estimated separately for each firm. The first pair of columns summarizes coefficients from regressions using all available data for each of the 367 firms with at least 20 observations in the sample window, 1970–2006. Numbers in parentheses are counts of firms with statistically significant (10%) coefficients. The second pair of columns uses 30-year rolling windows and includes firms with 20 or more in the window. The third pair of columns uses 20-year rolling windows and firms with 10 or more observations. The fourth pair of columns uses 10-year rolling windows and firms with five observations or more. Medians, equally weighted (EW) means and value-weighted (VW) means of coefficients are reported in the last three rows of each panel. The sample excludes firms with fiscal year-ends other than December and finance sector (SIC 6000–6999) firms.

2011) generates significance levels for a and b virtually identical to those obtained from clustering by year only. Thus, we evaluate the statistical significance of our estimated coefficients using year clustering.

Panel B of Table 3 presents these results. Regression 3B.1 shows a firm's stock return significantly positively correlated with its own firm-level TFP growth, but significantly negatively correlated with value-weighted aggregate TFP growth. Regression 3B.2 shows these results unaffected by including lagged value-weighted aggregate TFP growth as a control. Regressions 3B.3 and 3B.4 repeat these specifications, but use equally weighted aggregate TFP growth and, in 3B.4, its lagged value, along with firm-level TFP growth. Firm-level TFP growth again attracts a significant positive coefficient, and equally weighted aggregate TFP growth again attracts a negative coefficient.

Importance of spillover effect

This section evaluates the importance of aggregate TFP growth in explaining contemporaneous stock returns at the firm level. This entails running regressions of the form

$$r_{i,t} - r_{f,t} = \alpha_i + a_i d\pi_{i,t} + \beta_i \left(r_{m,t} - r_{f,t} \right) + \varepsilon_{i,t} \qquad (6)$$

removing aggregate TFP growth from the baseline model of Equation (3). By comparing the coefficient estimates of a_i and adjusted R^2 in Equations (3) and (6), we can assess the importance of the contribution of aggregate TFP growth in explaining contemporaneous firm-level stock return.

Table 4 shows the a_i estimates in Equation (6) to be generally smaller than those in Equation (3). Thus, the median a_i estimate based on the whole sample is 0.454 in Equation (3), but only 0.258 in Equation (6). Both the equal-weighted and value-weighted mean a_i estimates are also smaller: respectively, 0.404 and 0.100 for Equation (6) versus 0.575 and 0.201 for Equation (3). The adjusted R^2 statistics tell a similar story: the median regression R^2 based on the whole sample is 8.2% for Equation (3), but only 4.7% for Equation (6), the difference indicating a roughly 74% increase in goodness of fit from including aggregate TFP growth. The equal-weighted and value-weighted means of the regression R^2s are also markedly lower without aggregate TFP growth: 7.1% and 8.8%, respectively, for Equation (6) versus 10.6% and 10.9% for Equation (3). Similar patterns emerge using other estimation windows. This exercise suggests that omitting the aggregate TFP growth lowers the point estimates of a_i and underestimating the explanatory power of technology shocks on stock returns.

An alternative approach gauges the importance of aggregate TFP growth in the firm-level panel regression model of Equation (5). The results, reported in the last two columns of Panel B of Table 3, reinforce Table 4. For example, the adjusted R^2 rises from 7.4% to about 9.2% when aggregate TFP growth is included, representing a significant increase of about 25% in goodness of fit.

Robustness checks

The results in the tables and figures survive a battery of robustness tests. In all cases, *qualitatively similar* results means identical patterns of signs and significance to those in the tables and point estimates of roughly comparable magnitudes. Details are provided wherever this is not true.

The regressions in the tables utilize simple CAPM estimates of each stock's return each period. We repeat all these regressions using each of the following alternative specifications,

$$r_{i,t} = \alpha_i + a_i d\pi_{i,t} + b_i d\pi_{m,t} + \beta_i (r_{m,t} - r_{f,t}) + \varepsilon_{i,t} \tag{7A}$$

$$r_{i,t} = \bar{r}_i + a_i d\pi_{i,t} + b_i d\pi_{m,t} + \varepsilon_{i,t} \tag{7B}$$

$$r_{i,t} - r_{f,t} = \alpha_i + a_i d\pi_{i,t} + b_i d\pi_{m,t} + \sum_{f=1}^{3} \lambda_{i,f} f_f + \varepsilon_{i,t} \tag{7C}$$

$$r_{i,t} - r_{f,t} = \alpha_i + a_i d\pi_{i,t} + b_i d\pi_{m,t} + c_i d\pi_{j(i),t} + \beta_i (r_{m,t} - r_{f,t}) + \varepsilon_{i,t}. \tag{7D}$$

Specification (Equation (7A)) uses Black's (1972) zero-beta model in lieu of the CAPM; Equation (7B) employs a naïve specification in which each firm's expected stock return is assumed constant; Equation (7C) uses the Fama–French (1993) three-factor model. Equation (7D) includes the industry-level TFP variable, $d\pi_{j(i),t}$, the value-weighted average of the TFP growth rates of all firms in $j(i)$, the industry firm i belongs. An intermediate level of aggregation, industry-level data, might be of interest for several reasons. This removes any potential impact industry-level TFP growth might have on the coefficients of own firm-level TFP growth, a_i, and aggregate TFP growth, b_i.

Table 5 shows the distributional characteristics of the estimated response coefficients based on alternative specifications described above. Qualitatively similar results to those in Table 2 ensue in all cases. For Equation (7D), the c_i, like the b_i, have distributional characteristics consistent with winner-take-all competition. Roughly 56% of firms attract a negative c_i coefficient, whereas about 60% attract negative b_i coefficients in this specification. However, the greater incidence of positive c_i than b_i coefficients is also suggestive of relatively more positive spillovers within than between industries – perhaps because firms in an industry use more closely related technologies (Jaffe 1986; Bloom, Schankerman, and van Reenen 2013).

We generally aggregate firm-level response variables weighting by market capitalization. Using equal weighting generates qualitatively similar results. Weighting by assets or sales, rather than market capitalization also generates results qualitatively similar to those shown.

We drop observations for all firms with fiscal years ending in months other than December throughout so that the stock returns and accounting data, from which we construct TFP growth rates, match precisely. If we include all firms irrespective of their fiscal years ending, for example, the number of firms (firm-year observations) increased from 4672 (42,032) to 9389 (87,106) in the sample period. Rerunning our tests using all available data yields qualitatively similar results.

Finally, we consider alternative methods of calculating TFP. Basu and Fernald (1997) and Syverson (2004) modify the standard TFP calculation to account for firms not fully deploying their capital assets during business cycle downturns. This approach assumes materials and capital-in-production to be imperfect substitutes. Hall (1988) proposes a second alternative TFP calculation using revenue (rather than cost) shares. This approach imposes constant returns to scale. Both alternative TFP measures generate results qualitatively similar to those in the figures and tables.

IV. Alternative explanations

The results above expose a fallacy of composition. A firm's stock return is positively correlated with its firm-level TFP growth rate; but the stock market return is negatively correlated with aggregate-level

Table 5. Firms' stock returns explained by own and aggregate TFP growth: Alternative specification.

Panel A. Unadjusted for risk-free rate

	5A.1 Responses to own TFP (a)	5A.2 Responses to aggregate TFP (b)	5A.3 CAPM beta
Number of firms			
Negative	10,033 (863)	18,327 (2397)	9314 (488)
Positive	18,631 (3111)	10,337 (751)	19,350 (2363)
Total	28,664 (3974)	28,664 (3148)	28,664 (2851)
Median	0.453 (1.845)	−0.864 (−3.287)	0.393 (1.320)
Mean (EW)	0.871 (2.213)	−0.800 (−2.306)	0.447 (1.142)
Mean (VW)	0.358 (1.026)	−0.391 (−1.454)	0.395 (0.961)

Panel B. Without including CAPM factor

	5B.1 Responses to own TFP (a)	5B.2 Responses to aggregate TFP (b)
Number of firms		
Negative	9250 (789)	19,162 (2970)
Positive	19,414 (3498)	9502 (702)
Total	28,664 (4287)	28,664 (3672)
Median	0.498 (1.905)	−1.021 (−3.499)
Mean (EW)	0.834 (2.166)	−0.894 (−2.470)
Mean (VW)	0.380 (0.780)	−0.404 (−1.763)

Panel C. Including Fama–French three factors

	5C.1 Responses to own TFP (a)	5C.2 Responses to aggregate TFP (b)	5C.3 CAPM beta	5C.4 FF size factor	5C.5 FF book-to-market factor
Number of firms					
Negative	8740 (818)	14,838 (1696)	7708 (425)	10,330 (991)	10,401 (1291)
Positive	15,135 (2305)	9037 (701)	16,167 (2279)	13,545 (1792)	13,474 (1745)
Total	23,875 (3123)	23,875 (2397)	23,875 (2704)	23,875 (2783)	23,875 (3036)
Median	0.452 (1.844)	−0.705 (−3.033)	0.417 (1.362)	0.231 (1.332)	0.183 (0.790)
Mean (EW)	0.790 (1.917)	−0.748 (−2.016)	0.462 (1.269)	0.348 (1.089)	0.014 (−0.340)
Mean (VW)	0.412 (1.182)	−0.427 (−1.363)	0.467 (1.042)	−0.226 (−0.617)	0.072 (0.084)

Panel D. Including industry TFP

	5D.1 Responses to own TFP (a)	5D.2 Responses to aggregate TFP (b)	5D.3 Responses to industry TFP (c)	5D.4 CAPM beta
Number of firms				
Negative	8188 (673)	14,395 (1809)	13,387 (1706)	7315 (430)
Positive	15,687 (2686)	9480 (771)	10,488 (916)	16,560 (2077)
Total	23,875 (3359)	23,875 (2580)	23,875 (2622)	23,875 (2507)
Median	0.541 (2.350)	−0.698 (−3.442)	−0.422 (−3.380)	0.432 (1.350)
Mean (EW)	0.897 (2.600)	−0.541 (−1.712)	−0.709 (−2.734)	0.510 (1.236)
Mean (VW)	1.018 (2.174)	−0.093 (0.236)	−0.875 (−1.818)	0.451 (1.216)

Response coefficients are estimated for each firm. Coefficients in Panels A and B are estimated using 10-year rolling windows and firms with five observations or more and those in Panels C and D using for 10-year rolling windows and firms with seven observations or more. Numbers in parentheses are the number of firms statistically significant at the 10% level in the first three rows for each panel and the average coefficient of the firms statistically significant at the 10% level in the bottom three rows for each panel, respectively. The two rows from the bottom of each panel report both equally weighted (EW) and value-weighted (VW) means. The sample excludes firms with fiscal year-ends other than December and finance sector (SIC 6000–6999) firms.

TFP growth. The next subsection considers creative destruction as a potential explanation. The subsequent subsections reconsider alternative proposed explanations of the negative aggregate-level relationship between stock returns and measures of aggregate corporate sector profitability. These explanations differ in that they focus directly on the relationship between aggregate-level variables, rather than firm-level reactions to aggregate productivity growth.

Aggregation of creative destruction

This seeming inconsistency arises because a firm's stock return is affected not just by its own innovation, but also by the innovative activity of other firms. Rival firms' success with productivity-enhancing innovations is bad news, not good news, for any individual firm.

The puzzle is that a firm's TFP growth elevates its stock price because higher productivity means changed production function parameters that let the firm produce more valuable outputs from the same inputs (product innovation) or the same outputs from less costly inputs (process innovation), or some mixture of the two. Regardless of the details, an increase in aggregate TFP growth likewise lets the economy produce more with less, and this, virtually by definition, is a Pareto improvement that should create value overall. Negative b_i might predominate in firm-level regressions (Equation (3)), but the contribution of the winners to the overall economy should eclipse the losses suffered by the losers.

Reconciling this reasoning with our findings requires returning to the discussion of 'winner-take-all' competition. This form of competition bestows huge rewards on a handful of creative winner firms, but wreaks devastation upon vastly more loser firms. This devastation can take several forms. First, shareholders foresee loser firms' future cash flows falling as innovation-driven competition intensifies. Second, shareholders foresee decreases in the values of loser firms' existing physical capital, production routines and managerial talent – all of which were designed for older technology. Third, both of the above effects can increase loser firms' financial and/or operating leverage, which would further erode share values if shareholders foresee substantial bankruptcy costs. Fourth, a successfully innovative firm's profits need not all accrue to its public shareholders if its creative insiders pay themselves an entrepreneurial rent (e.g. patent royalties). All four considerations, given the forward-looking nature of share prices, permit immediate price drops in technology loser firms' stocks to appear disproportionately large relative to their immediate productivity drops. Regardless of the mechanism, some part of the Pareto gains from aggregate TFP growth can readily accrue to people other than the winner firms' public shareholders at the time its TFP growth is observed.

Time-varying discount rates

Kothari, Lewellen, and Warner (2006) note that stock prices are the expected present discounted values of future corporate disbursements, and argue that, if investors' discount rates rise sufficiently whenever aggregate corporate earnings rise, the net effect might be lower stock market valuations. This thesis requires that investors have not just time-varying risk aversions (Fama 1991; Campbell, Lo, and MacKinlay 1997), but they discount future risky cash flows *more* steeply in good times than in bad times. To test their thesis, Kothari, Lewellen, and Warner (2006) construct several discount rate proxies: the 30-day T-bill rate, the difference between 10-year and 1-year constant maturity treasury rates and the difference between Moody's Baa and Aaa yields. Because the stock market return correlates negatively with aggregate earnings throughout their sample window, their thesis predicts positive correlations between their discount rate proxies and aggregate earnings. Their results are inconclusive: aggregate earnings growth correlates significantly positively with the T-bill rate, insignificantly with the term structure variable and significantly negatively with the bond risk premium variable. Hirshleifer, Hou, and Teoh (2009) conduct a similar analysis and arrive at similarly inconclusive results. Also, although the relationship between the stock market return and aggregate earnings growth is negative during their sample period, the relationship turns positive in part of our longer sample window.

Our explanation based on creative destruction and displacement risk can explain the negative relationship between the stock market return and aggregate earnings. Suppose average firm earnings grow while the performance gap between winner and loser firms' earnings widens. As noted above, loser firms' stock prices might fall because of the innovation-driven negative spillover effect (their earnings fall as they lose business to more innovative firms or shareholders discount the value of their capital more heavily). If displacement risk is a systematic risk factor disproportionately affecting loser firms' stocks, intensified creative destruction could disproportionately elevate the discount rates investors use to value loser firms. Thus, our creative destruction explanation may be an elaboration of the discount rate thesis of Kothari, Lewellen, and Warner (2006) and Hirshleifer, Hou, and Teoh (2009), not a rival explanation. If most listed firms are losers in races to adopt new technologies, their discount rates might increase in general, as those papers posit. If the pace of innovation picks up and falls off again, the displacement risk factor might wax and wane as well, explaining the sign flip we observe.

Other explanations

Hirshleifer, Hou, and Teoh (2009) decompose earnings into cash flow and accrual's components, and show that the contemporaneous negative relationship between earnings growth and stock returns is driven by accrual rather than cash flow component. We replicate their findings using their sample period, but not outside it. One possibility is that regulatory reforms around the turn of the 21st century altered the practice of accruals management in ways that somehow reversed the negative relationship between stock market returns and aggregate earnings, at least for a time. The details of such an explanation are not immediately obvious, but their hypothesis cannot be rejected out of hand.

Sadka and Sadka (2009) posit that investors foresee aggregate earnings growth more clearly than firm-level earnings growth. If so, firm-level earnings would convey new information and contemporaneously affect stock returns; but aggregate earnings, largely known in advance, would not. Invoking Campbell's (1991) return decomposition, they derive a negative aggregate-level relationship between expected earnings growth and the expected stock market return. This requires that investors demand a lower risk premium whenever they expect positive earnings growth (Chen 1991) and Sadka and Sadka (2009) present empirical results supporting this. This hypothesis may also be correct; but is not obviously a complete explanation. For example, if the predictability of aggregate earnings is a major driving force for the negative relationship, the positive relationship observed after 2000 suggests a decreased predictability of aggregate earnings during that period despite institutional reforms to increase transparency.

We suggest that Okham's razor favours a time-varying negative spillover effect as the simplest explanation of not just the *fallacy of composition*, but also its changing characteristics over time. Nonetheless, we welcome further research into the importance of earnings management and the differential predictability of aggregate versus firm-level fundamentals.

V. Conclusions

Aggregate productivity growth, which many macroeconomists interpret as good news for the economy, may not be good news for shareholders (Ritter 2012). While some firms' shares do rise with aggregate TFP growth, most firms' shares drop. This implies that high aggregate productivity growth can be bad news for the shareholders of most firms and, because losers can outweigh winners in the stock market as a whole, for shareholders who hold market portfolio.

The declines in most firms' share prices associated with increased aggregate productivity growth highlight the economic importance of negative spillovers from technological innovation. These price drops might reflect either technology laggards facing intensified competition that erodes their earnings and future earnings growth opportunities or the market discounting technology laggards' future earnings more heavily to reflect their greater risk of being left behind. Our results also support papers emphasizing winner-take-all competitions in corporate sectors, which claim that handful of winners outperform most firms, destroying their values as empirically.

In firm-level regressions explaining stock returns, the coefficients of aggregate productivity growth are predominantly negative, while the coefficients of the firm's own productivity growth are predominantly positive. This suggests an explanation for a *fallacy of composition* that stock returns and earnings growth correlate positively in firm-level data, but negatively in aggregate data (Kothari, Lewellen, and Warner 2006). This seeming contradiction is readily explicable in that earnings and TFP growth both gauge a firm's ongoing profitability, and merely reflects a preponderance of listed firms' stock returns correlating negatively with aggregate productivity growth. These negative aggregate effects sum to a negative correlation between the market return and aggregate productivity growth; despite each firm's stock return correlating positively with the firm's own productivity growth. Unlike alternative explanations, this thesis also explains observed variation in the magnitudes of these firm-level and aggregate-level effects both across firms and over time.

Taken at face value, our empirical findings imply a predominantly negative effect of aggregate productivity growth on the portfolio wealth of highly diversified public shareholders in the late 20th century. This may reflect public shareholders being precluded from diversifying into early stage start-ups, and even experiencing a significant wealth loss as economy-wide innovations unfold. Our estimation techniques require that we exclude very young firms from the analysis that leads to this conclusion, so if these firms provide very high returns, public shareholders might share more fully in the fruits of technological progress. However, younger firms' post-IPO long-run returns are negative on average (e.g. Ritter 1998), suggesting that holding more younger stocks would not have left public shareholders wealthier.

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