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Hyunbae Chun
Jung-Wook Kim
Randall Morck

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ABSTRACT

Technological innovation is not a blessing for all firms, or for investors holding the market. In the late 20th century US, individual firms' stock returns correlate positively with their own productivity growth, yet the market return correlates negatively with aggregate productivity growth, yet. 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. Analogous reasoning explains prior findings that the market return correlates negatively with aggregate earnings.

Hyunbae Chun
Department of Economics
Sogang University
Seoul 121-742 Korea
hchun@sogang.ac.kr

Jung-Wook Kim
Associate Professor of Finance
College of Business Administration
Seoul National University
Seoul, Korea
151-742
jwkim87@snu.ac.kr

Randall Morck
Faculty of Business
University of Alberta
Edmonton, AB T6G 2R6
CANADA
and NBER
randall.morck@ualberta.ca

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

1. 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 through 2006 let us explore the contemporaneous relationships between firm-level and aggregate stock returns and productivity growth rates. This exercise reveals why the sign of the relationship between stock return and growth in earnings (an accounting measure of profits) at the firm-level reverses at the aggregate-level (Kothari, Lewellen, and Warner, 2006; Hirshleifer, Hou, and Teoh, 2009; Sadka and Sadka, 2009; Ritter, 2012) by supplementing recent theoretical and empirical work revealing economically significant *negative spillovers* from technological innovation on established firms (Hobjin and Jovanovic, 2001; Gârleanu, Kogan, and Panageas, 2012; Gârleanu, Panageas, and Yu, 2012; Kogan and Papanikolaou, 2012a, 2012b).

Work in productivity growth emphasizes *positive spillovers* from technological innovation. Popular endogenous growth models (Aghion and Howitt, 1992; Romer, 1986) 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

[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.

shareholders (Jaffe, 1986; Bernstein and Nadiri, 1989; Griliches, 1992). For example, AT&T's 1970s semiconductor innovations first spilled over into electronics parts firms, and then to other sectors, including autos, home appliances, retailing, and watchmaking (Ruttan, 2001).

However, more 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.[2] Tirole (1988) dubs these negative spillovers the *business stealing effect* of innovation. Yet other work characterizes technological progress as *winner-take-all competition*, where a lone winner amasses immense wealth and there is no prize for second place.[3] Consistent with negative spillovers in the semiconductor sector, Megna and Klock (1993) document firms' share prices dropping markedly on news of a rival's innovation success. Lerner (1997) finds evidence of winner-take-all competition among hard-disk makers.

This work recalls Schumpeter's (1912) view of innovation as a process of *creative destruction.* Like Romer (1986), 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. Moreover, another entrant, or even a seeming loser today, might ultimately adapt, imitate, or improve on the innovation to emerge as tomorrow's creative winner, wreaking value destruction upon the initially successful innovator.

[2] See David (1990), Davis and Haltiwanger (1992), King and Levine (1993), Jovanovic and MacDonald (1994), Helpman and Trajtenberg (1998a, 1998b), Greenwood and Jovanovic (1999), Hobijn and Jovanovic (2001), Chun, Kim, Morck, and Yeung (2008), Fogel, Morck, and Yeung (2008), and Bena and Garlappi (2012).

[3] Merton (1968) first characterized winner-take-all competition as the *Matthew Effect*, referring to Matthew 13:12 "*For whoever hath, to him more shall be given, and he will have an abundance; but whoever hath not, even what he hath shall be taken from him*." See also Dasgupta and Maskin (1987), Arthur (1990), Cook and Frank (1996), Stephan (1996), Bena and Garlappi (2012), and Kogan, Papanikolaou, Seru, and Stoffman (2012).

This destructive aspect of technological progress could become especially important amid the diffusion of a *general purpose technology* (GPT), a new technology that lets innovative firms in most (or many) sectors, rather than just one (or a few), raise their productivity, ultimately enhancing economic growth across the board. Jovanovic and Rousseau (2005) argue that the information technology (IT) boom of the 1990s is a recent example of a GPT.[4] Hobijn and Jovanovic (2001) show the introduction of a GPT favoring new firms over incumbents with old technologies embedded in existing capital or attuned to obsolescing value chains. Thus, Gârleanu, Kogan, and Panageas (2012) model broad-based technological progress inducing *displacement risk*, an erosion in the values of established firms' physical (and human) capital. Gârleanu, Panageas, and Yu (2012) and Kogan and Papanikolaou (2012a, 2012b) show firms' decisions about investing in a new GPT widening the performance gaps between winner and loser firms, increasing cross-sectional dispersion in firm-valuation.[5] A common theme of these papers is that, while technological innovation has the bright side of ultimately increasing overall, or average, firm productivity, it also has a dark side of destroying, at least partially, the values of the many established firms that are left behind.

To explore these issues, we measure the spillover effect of technological innovation by contrasting stock returns at the firm- and economy-levels. Our sample is Center for Research in Security Prices (CRSP) and Compustat firms from 1970 to 2006.[6] We follow the growth theory literature in using firm-level total factor productivity (henceforth, TFP) growth as a proxy for

[4] Earlier examples include the steam engine, electricity, the internal combustion engine and electronics (Bresnahan and Trajtenberg, 1995; Jovanovic and Rousseau, 2005).
[5] Note that the gap between winners' and losers' stock returns can be wider than that between their measured productivity growth rates because of the forward-looking nature of stock returns.
[6] Our sample period ends in 2006, because the Bureau of Economic Analysis (BEA) and the Bureau of Labor Statistics (BLS) ceased reporting SIC-based industry-level deflators thereafter. The newly introduced NAICS-based industry classification is unavailable before 1987.

economically profitable technological innovation; and the finance literature in using stock returns to measure changes in firms' market values, as in Kothari, Lewellen, and Warner (2006).[7] TFP is defined as the ratio of total real revenue to the total real costs of all factors of production, including both labor and capital. TFP differs from accounting earnings in subtracting the estimated required return to shareholders as an annualized dollar cost and in subtracting estimated economic depreciation, rather than accounting depreciation and amortization.[8] 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 heterogeneous, albeit mostly negative, reaction to aggregate TFP is evident in most industries, suggesting that negative spillovers are not limited to certain high-tech sectors. These findings extend Kogan, Papanikolaou, Seru, and Stoffman (2012), who find that firms' stock returns are negatively affected by other firms' innovation activities measured by patents.

Second, this heterogeneous, but mainly negative, firm-level reaction to aggregate TFP growth explains a recent *fallacy of composition* finding: US firms' stock returns and earnings are correlated positively, but the US stock market return and aggregate corporate earnings are negatively correlated (Kothari, Lewellen, and Warner, 2006; Hirshleifer, Hou, and Teoh, 2009; Sadka and Sadka, 2009). 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 firm's stock returns with aggregate TFP growth. The firm-level correlation, in contrast, reflects a consistently positive

[7] Section 2.2 discusses other innovation measures used in the literature.
[8] See section 2.1 for further discussion on the construction and interpretation of TFP.

linkage between a firm's own TFP growth and its own stock's return. Accounting earnings approximate economic profits closely enough to echo this pattern. Our explanation of this fallacy of the composition is based on firm-level evidence; and thus supplements prior explanations based on aggregate-level data.[9]

Third, observed negative spillovers exhibit substantial time-series variation. The gap between firms whose stock prices rise with aggregate productivity growth and those whose stock price fall expands until 2000 and then gradually narrows. This accords with the IT boom of the 1990s inducing a wave of creative destruction across the U.S. economy that largely ran its course by the turn of the century (Pástor and Veronesi, 2009). The relationship between the stock market return and aggregate earnings growth found by Kothari, Lewellen, and Warner (2006) tracks this timing: it grows increasingly negative through the 1990s, and then subsides and even flips signs.

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 (Gompers, Kovner, Lerner, and Scharfstein, 2008). Public investors who buy into IPOs tend to earn modest returns (Ritter and Welch, 2002; Gompers and Lerner, 2003). Our result is consistent with these findings, in that public shareholders' wealth, represented by the

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[9] Kothari, Lewellen, and Warner (2006) suggest that the positive relationship between discount rate and earnings growth at the aggregate level may be an underlying reason for the discrepancy, but find little empirical support for the hypothesis. Hirshleifer, Hou, and Teoh (2009) show that Kothari, Lewellen, and Warner (2006)'s result is driven by the accruals component of aggregate earnings. Sadka and Sadka (2009) focus on the fact that stock prices predict earnings better at the aggregate-level than at the firm-level. None of these approaches let individual firms react heterogeneously to a common aggregate productivity shock, which underlies explanation. See section 4.2 for more discussion on these papers.

market return, can decline as economy-wide innovations unfold.

Our findings also suggest that understanding aggregate-level correlations requires understanding firm-level dynamics. Theoretical and empirical work transcending representative firms with heterogeneous firm-level dynamics might be highly illuminating.

This paper is organized as follows. Section 2 describes the data. Sections 3 reports empirical findings. Section 4 discusses implications of our findings and section 5 concludes.

2. Data

2.1 Total Factor Productivity Growth Measure

A successful innovation alters the innovating firm's production function, letting it either produce more valuable output from given inputs (product innovation) or a given output from less costly inputs (process innovation). In either case, the firm's total factor productivity (TFP) grows: the value of its output rises relative to the costs of its inputs. This echo's Schumpeter's (1912) argument, that innovation, by altering the parameters of production, places the economy in disequilibrium. Until output and factor prices adjust to a new equilibrium, the innovating firm earns economic profits, or quasirents, equal to the value of its outputs minus the cost of its inputs. In either perspective, the productivity gains or quasirents can alternatively be thought of as a return to creativity due the entrepreneur, or perhaps shared with initial capital providers as a reward for their ability to identify promising early-stage innovations.

This alteration to the parameters of a production function is the essence of technological change, indeed of innovation in general (Schumpeter, 1912). Thus, TFP growth can arise from successfully accessing new markets, providing improved services, or any number of non-technological innovations to previously state-of-the-art business practice, as well as from engineering advances. The deep connection to economic profits and innovation makes TFP growth a key variable in economic growth theory (Romer, 1986, 1990; Grossman and Helpman, 1991; Aghion and Howitt, 1992, 1997; Aghion, Harris, Howitt, and Vickers, 2001).

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

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

where $dY_{i,t}, dL_{i,t}$, and $dL_{i,t}$ are firm *i*'s growth rates in value-added, labor, and capital, respectively and where $S_{L,i,t}$ and $S_{K,i,t}$ are the share of the firm's costs payable to its providers of labor and capital, respectively.[10] 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 *labor 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 2-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 construct substitutes. Our *output growth rate* is then $dY_{i,t} \equiv \ln(Y_{i,t}) - \ln(Y_{i,t-1})$.

[10] In constructing TFP growth measure, we use the definition used by BLS. However, as robustness checks, we use other methods of calculating TFP growth as suggested by Hall (1988) and Basu and Fernald (1997) as discussed in section 3.4.

The firm's labor cost share, $S_{L,i,t}$, is its *labor and related expenses* over this plus *capital services costs*. If *labor 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 *labor 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* (FRTW) 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 (2011) 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 *labor 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.

2.2 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. Schoar (2002) and Maksimovic and Phillips (2002) compare TFP in diversified firms versus conglomerates. İmrohoroğlu and Tűzel (2013) relate firm-level TFP to stock return. Vassalou and Apedjinou (2004) and Lieberman and Kang (2008) show TFP variable to contain information above and beyond that discern able from earnings. Chun, Kim, Morck, and Yeung (2008) and Chun, Kim, and Morck (2011) link TFP variation to stock return volatility.

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

(Blundell, Griffith, and van Reenen, 1999; Hsu, 2009; Bena and Garlappi, 2012; Kogan, Papanikolaou, Seru, and Stoffman, 2012; Hirshleifer, Hsu, and Li, 2013) or R&D (Chan, Lakonishok, and Sougiannis, 2001; Hsu, 2009; Lin, 2012; Hirshleifer, Hsu, and Li, 2013). 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.[11] Second, recent work shows that some 50% of patents are strategic – designed as tolls along rivals' possible research paths, preemptive moves to avoid litigation or cross-licensing, or defensive gambits to thwart rivals' research efforts (Hall and Ziedonis, 2001; Gambardella, Giuri, and Luzzi, 2007; Motohashi, 2008). Third, many economically important innovations are not patented because the innovator prefers alternative intellectual property defenses – secrecy, complex design, or speedy product development (Levin, Klevorick, Nelson, and Winter, 1987; 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 costs of successful and unsuccessful firms' innovative activity. 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

[11] To overcome this issue, Kogan, Papanikolaou, Seru, and Stoffman (2012) calculate a quality adjusted patent measure by incorporating stock market reaction of a firm when a patent is granted to the firm.

measure of the ex-post gains due to successful innovation of any kind.

2.3 Stock Returns

When public shareholders learn that a firm risks losing business to more innovative or productive competitors (Tirole, 1988) – the phenomenon Gârleanu, Kogan, and Panageas (2012) dub *displacement risk* – 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 (Hobijn and Jovanovic, 2001; Mazzucato, 2006).

To construct stock returns, we begin with all stocks covered by the CRSP from 1970 through 2006 that have matching TFP growth rates. 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 four-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.

[Table 1 about here]

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.

3. Empirical Results

3.1 Firm-level Regressions

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

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

where $\hat{r}_{i,t}$ firm *i*'s realized abnormal stock return in year *t*, equals the firm's observed total stock return, $r_{i,t}$, minus its expected value, $E[r_{i,t}]$ estimated by CAPM 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 $d\pi_{i,t}$. 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 (business stealing effect) 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 [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), Hall (1993), and Blundell, Griffith, and van Reenen (1999) find higher shareholder value in firms with higher R&D or patents. İmrohoroğlu and Tűzel's (2013) 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.

[12] Including the lagged value of $d\pi_{m,t}$ in [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.

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, the *business stealing effect* (Bena and Garlappi 2012; Gârleanu, Kogan, and Panageas, 2012) suggests that most firms' b_i should be negative.

To operationalize [2], we estimate the following regression separately for each firm using annual data windows of various lengths,

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

In [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 $r_{f,t}$ the annualized one-month Treasury Bill return, $r_{m,t}$ the CRSP value-weighted annual market return, and β_i stock i's estimated CAPM beta.[13] The intercept α_i captures any remaining unexplained component in the firm's stock return.

[Table 2 about here]

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

[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 [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 [2] yields qualitatively similar results. See section 3.4 for details.

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 [3], but eliminates firms founded after 1986 and thus obviously misses major innovative entrants during the 1990s IT boom. We therefore rerun [3] for each firm using sequentially increasingly inclusive sampling criteria and shorter estimation windows. The third and 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; and the fourth pair of columns uses 10-year rolling windows and firms with 5 observations or more.

First, consider the leftmost two columns, which summarize the coefficients for firm-level regression [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.[14]

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

[14] Estimating regression for each firm and counting significant coefficients fails 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 3.3 for details.

first pair of columns, the equally-weighted mean of the a_i, is 0.575, and exceeds its value-weighted analog, 0.201. The equally-weighted mean of the b_i is -0.955, and likewise exceeds its value-weighted analog 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.

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. Panels C1 and C2, respectively, of Figure 1 show the distributions of all the β_i coefficients and of those significant at 10% or better.

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 [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.[15] 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 [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 5 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% (3,076 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.

[Figure 1 about here]

[15] 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 3.3), 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.

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.[16] 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 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 U.S. by about 2002. Kogan, Papanikolaou, Seru, and Stoffman (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

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

of the b_i, for which we can test.

[Figure 2 about here]

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 cutoffs 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 cutoffs.

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 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.

Panels A3 and B3 of Figure 2 show the difference between 9th and 1st decile cutoffs 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 that the difference between 9th and 1st decile cutoffs 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, 2003, 2005).

[Figure 3 about here]

Figure 3 reports the empirical probability functions of firms' b_i, averaged across 1980 through 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.[17] Figure 3 shows that the negative 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 time 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.

3.2 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,

[17] One sector lacks significant coefficients.

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

This specification follows from summing the regressions [2] across all firms, weighting each by w_i.[18] 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 [2]. Thus, if positive spillovers outweigh negative spillovers across firms, the weighted average $b \equiv \sum_i w_i b_i > 0$; but if negative spillovers – the business stealing effect predominates, $b < 0$.[19] 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.

[Table 3 about here]

[18] Summing both sides of [2], weighting by w_i = firm i's prior year-end market capitalization, yields $\sum_i w_i \hat{r}_i \equiv r_{m,t} - E[r_{m,t}] = \sum_i w_i a_i d\pi_{i,t} + d\pi_{m,t} \sum_i w_i b_i$. This leads to [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, [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.

[19] 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 behavior (see especially Figure 4 below).

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 growth as a control leaves this result qualitatively unchanged.[20, 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.

[Figure 4 about here]

To explore the stability of b over time, Figure 4 plots estimates of the b coefficient from [4] over successive ten-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 [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 b_i coefficients is generally more negative than its value-weighted analog, 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.

[20] Here and throughout, we define *qualitatively unchanged* to mean an identical patterns of signs and significance and point estimates of roughly comparable magnitude.

[21] 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.

3.3 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 [3] the a_i are generally positive and the b_i are generally negative. Moreover, the aggregate productivity growth coefficient b in [4] closely tracks the means of the firm-level coefficients on aggregate productivity growth, b_i, in [2], operationalized as [3]. These patterns suggest the alternative specification of panel regressions of the form,

[5] $$r_{i,t} = \sum_i \delta_i + a d\pi_{i,t} + b d\pi_{m,t} + \varepsilon_{i,t}$$

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 coefficient 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 [5], though more restrictive in requiring the firm-level coefficients in [3] to be identical across firms and across time ($a_i = a$ and $b_i = b$ for

[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.

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). These considerations both weigh against finding statistical significance in [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, 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.

3.4 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

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

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,

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

[6B] $r_{i,t} = \bar{r}_i + a_i d\pi_{i,t} + b_i d\pi_{m,t} + \varepsilon_{i,t}$

[6C] $r_{i,t} - r_{f,t} = \alpha_i + a_i d\pi_{i,t} + b_i d\pi_{m,t} + \sum_{f=1}^{3} \lambda_{i,f} f_f + \varepsilon_{i,t}$

[6D] $r_{i,t} - r_{f,t} = \alpha_i + \beta_i \left(r_{m,t} - r_{f,t} \right) + a_i d\pi_{i,t} + b_i d\pi_{m,t} + c_i d\pi_{j(i),t} + \varepsilon_{i,t}$.

Specification [6A] uses Black's (1972) zero-beta model in lieu of the CAPM; [6B] employs a naïve specification in which each firm's expected stock return is assumed constant; and [6C] uses the Fama-French (1993) three-factor model. [6D] 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 remove 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 4 about here]

Table 4 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 [6D], 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 their fiscal years ending, for example, the number of firms (firm-year observations) increased from 4,672 (42,032) to 9,389 (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 Kimball (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.

4. 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 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.

4.1 The 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 [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.[24] First, shareholders foresee loser firms' future cash flows falling as the business stealing effect of innovation takes hold (Tirole, 1988). 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 (Hobijn and Jovanovic, 2001; Gârleanu, Kogan, and Panageas, 2012; Gârleanu, Panageas, and Yu, 2012; Kogan and Papanikolaou; 2012a, 2012b). Third, both of the above effects can increases 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.

4.2 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 it investors' discount rates rise sufficiently whenever aggregate corporate earnings rise, the net effect might be lower stock

[24] See Hobijn and Jovanovic (2001), Jovanovic and Rousseau (2003), Laitner and Stolyarov (2003), Rajan and Zingales (2003, 2004), Gârleanu, Kogan, and Panageas (2012), Gârleanu, Panageas, and Yu (2012), and Kogan and Papanikolaou (2012a, 2012b).

market valuations. This thesis requires that investors have not just time-varying risk premiums (Fama, 1991; Campbell, Lo, and MacKinlay, 1997), but that 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 ten-year and one-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.

Kothari, Lewellen, and Warner (2006) and Hirshleifer, Hou, and Teoh (2009) suggest a no mechanism whereby investors might increase their discount rates when aggregate earnings rise. If creative destruction underlies the negative relationship between the stock market return and aggregate earnings, such a mechanism appears. 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 a business stealing effect (their earnings fall as they lose business to more innovative firms) or a displacement risk effect (shareholders discount the value of their capital more heavily), or both. 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 technology, innovation might raise discount rates 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.

4.3 Other Explanations

Hirschleifer, 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 too may also correct; but is not obviously a complete explanation. Here too, time variation in the contemporaneous relationship between aggregate profits and stock market returns, evident in Figure 4, would appear to require a more complicated model.

We suggest that Okham's razor favors 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.

5. Conclusions

High aggregate productivity growth appears to be bad news for many firms. While some firms' shares do rise with aggregate TFP growth; those of most firms drop. This predominance of negative relationships leads to several major conclusions.

First, the result supports Schumpeter's (1912) concept of creative destruction driving aggregate productivity growth and validates formal models of that process (Tirole, 1988; Gârleanu, Kogan, and Panageas, 2012). These findings also reinforce work by Bena and Garlappi (2012) and Kogan, Papanikolaou, Seru, and Stoffman (2012), showing a very few firms to be responsible for most innovation, as measured by patents in the U.S.

Second, this lopsided and predominantly negative distribution of firm-level associations with aggregate productivity growth explains a *fallacy of composition*: firms' stock returns correlate positively with their own TFP growth rates, but the stock market as a whole correlates negatively with aggregate TFP growth. This seeming contradiction reflects a preponderance of listed firms' stock returns correlating negatively with aggregate productivity growth, and summing up to generate a negative aggregate correlation. This fallacy of composition may explain, partially at least, the seemingly discordant findings of Kothari, Lewellen, and Warner (2006), Hirshleifer, Hou, and Teoh (2009), and Sadka and Sadka (2009) that stock returns and earnings growth correlate positively at the firm level, but negatively at the aggregate level. This parallelism is unsurprising because TFP and earnings are both proxies for profits.

Third, this reconciliation highlights firm-level inequality as regards the benefits of technological change. Taken at face value, the empirical findings suggest a predominantly negative effect of aggregate productivity growth on the portfolio wealth of highly diversified public shareholders. This may reflect public shareholders being precluded from diversifying into early-stage start-ups and even experience significant wealth loss as economy-wide innovations unfold if asset prices are set by marginal investors who do have access to the full spectrum of diversification possibilities. Our estimation techniques require that we exclude very young firms from the analysis that leads to this conclusion, so if these firms provided very high returns, public shareholders might share more fully in the fruits of technological progress. However, Ritter (1998) finds strongly negative post-initial public offering performance for younger firms, suggesting that holding the excluded stock would leave public shareholders with even lower returns.

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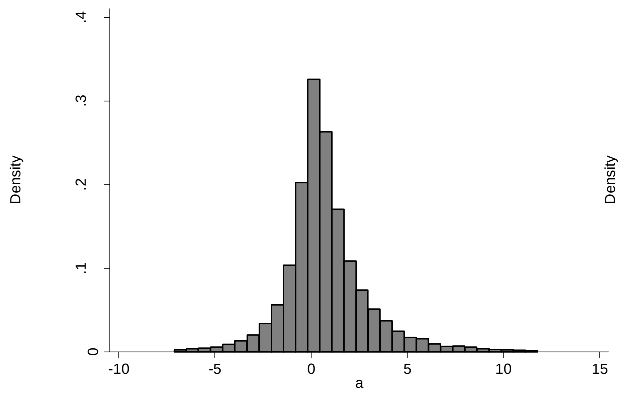
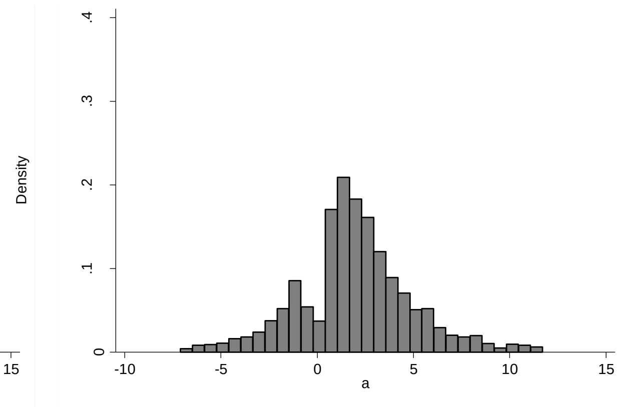
Figure 1. Distributions of Firms' Stock Return Responses to Own and Aggregate TFP Growth

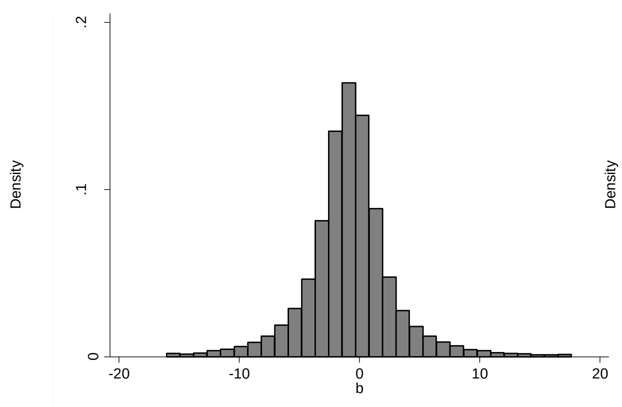
Panel A1. Firm-level TFP: All Firms



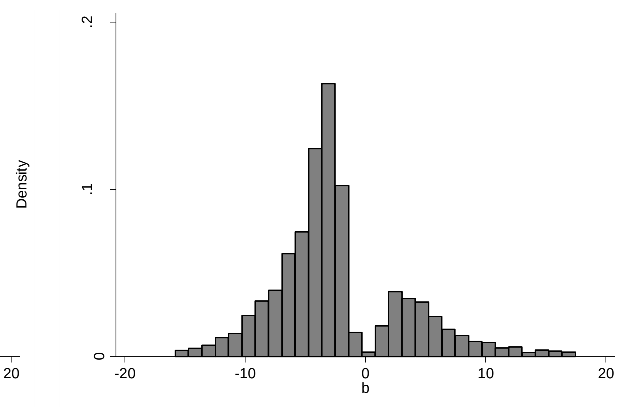
Panel A2. Firm-level TFP: Significant at 10%



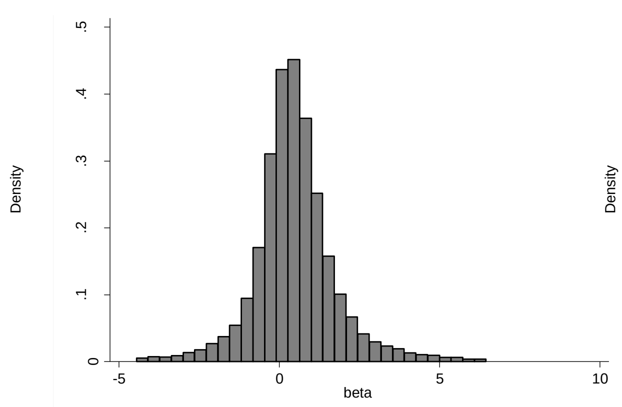
Panel B1. Aggregate TFP: All Firms



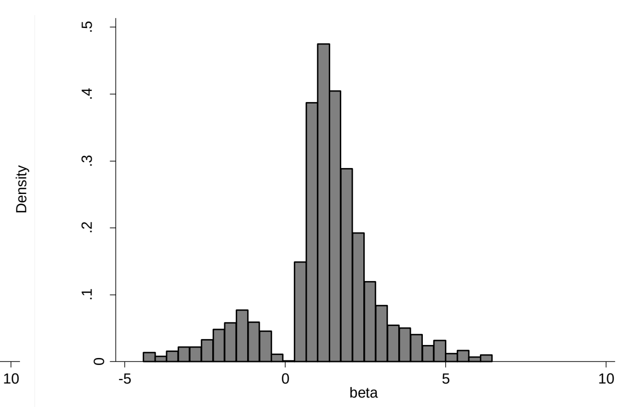
Panel B2. Aggregate TFP: Significant at 10%



Panel C1. CAPM Beta: All Firms

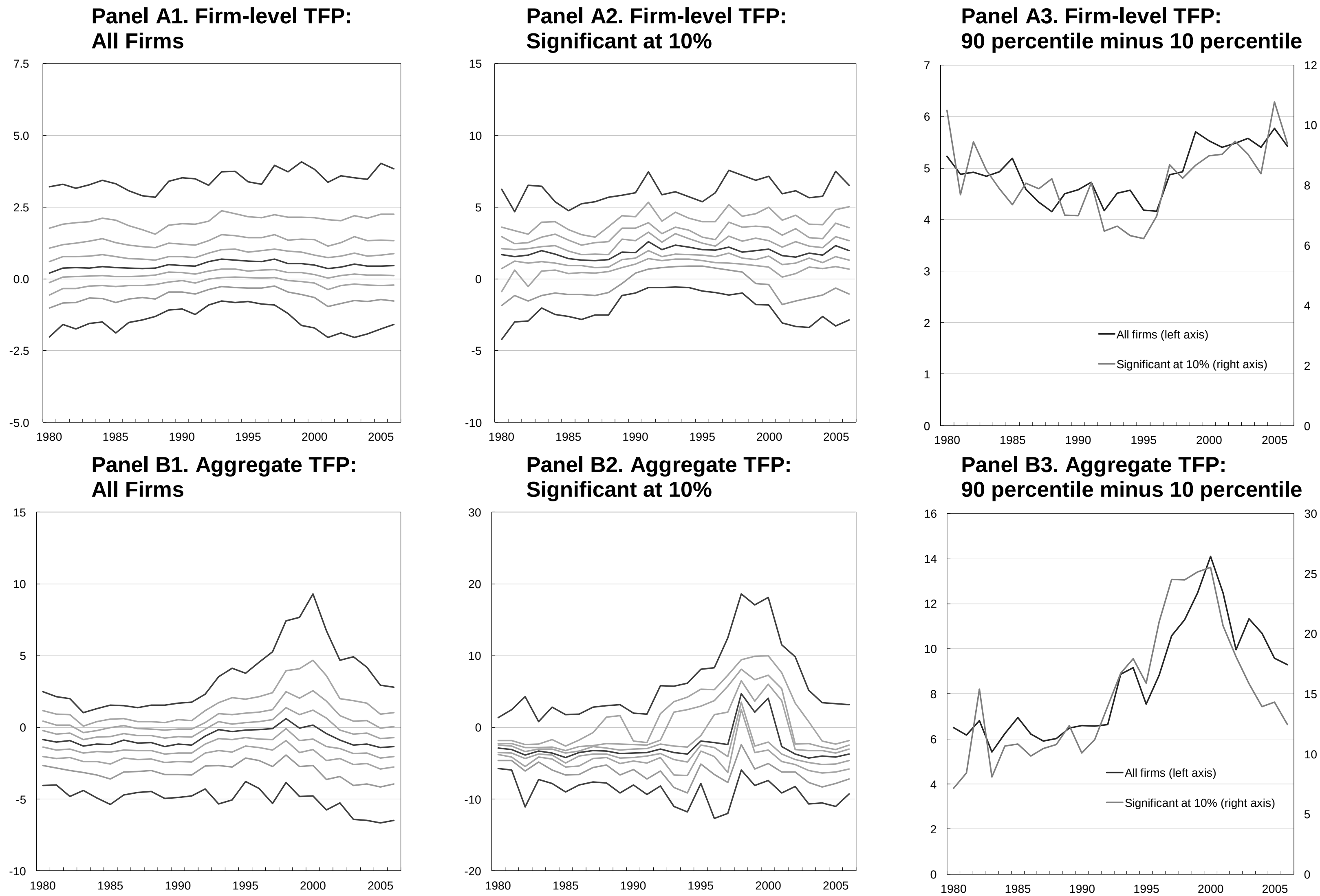


Panel C2. CAPM Beta: Significant at 10%



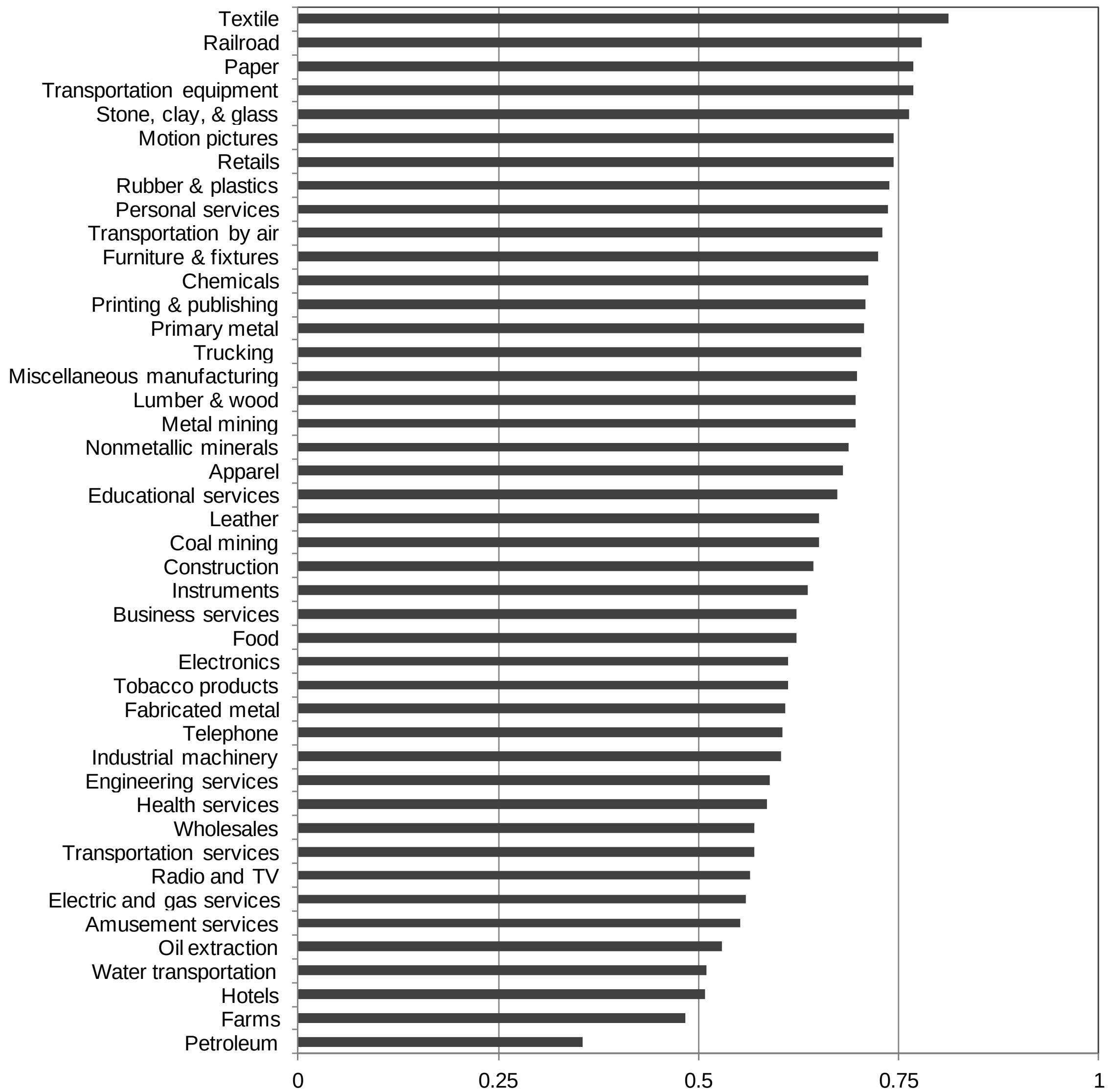
Notes: Figures omit top and bottom 1% of estimated coefficients.

Figure 2. Dispersion in Firm-level Stock Return Responses to Own and Aggregate TFP Growth



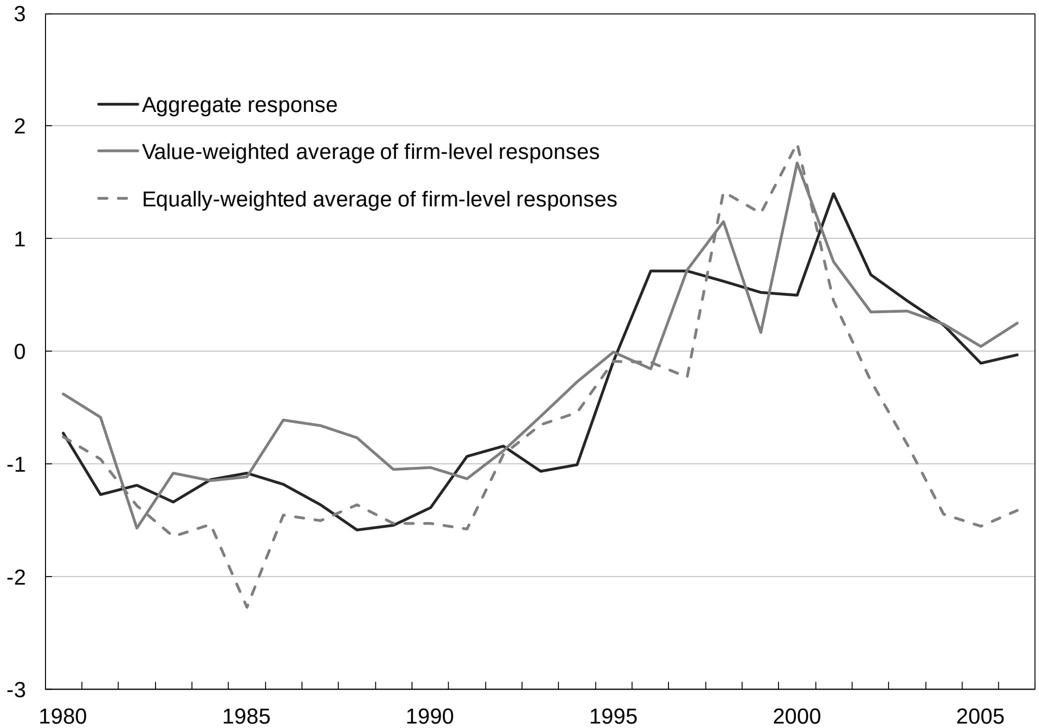
Notes: Figures show decile cutoffs of firm-level stock return response to aggregate TFP growth. In Panels A1, A2, B1, and B2, the three black lines, from the bottom up,,track 10th, 50th (median) and 90th percentiles, respectively, by the end-year of each 10-year estimation window. Gray lines represent intermediate deciles. Panels A1 and B1 include all firms and Panels A2 and B2 include only firms with coefficients significant at 10%.

Figure 3. Fraction of Firms with Negative Stock Return Response to Value-Weighted Aggregate TFP Growth, Means over 1980–2006 by Industry



Notes: Each bar indicates the proportion of firms with negative beta averaged over the sample period of 1980–2006. The sample includes all industries with 3 or more firms in 1980–2006.

Figure 4. Aggregate-level versus Mean Firm-level Stock Return Responses to Aggregate TFP Growth in Rolling Ten-year Windows Ending in the Year Indicated



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

Table 1. Summary Statistics, 1970–2006

Panel A. Aggregate Level

	Mean	Stdev	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	Stdev	Mean	Stdev	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

Notes: 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.

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 firms								
Negative	94	(13)	678	(85)	3,337	(333)	9,899	(858)
Positive	273	(87)	1,991	(573)	8,978	(2,253)	18,765	(3,186)
Total	367	(100)	2,669	(658)	12,315	(2,586)	28,664	(4,044)
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 firms								
Negative	297	(96)	2,139	(630)	8,598	(1,660)	18,000	(2,278)
Positive	70	(5)	530	(24)	3,717	(219)	10,664	(798)
Total	367	(101)	2,669	(654)	12,315	(1,879)	28,664	(3,076)
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 firms								
Negative	54	(1)	506	(27)	3,248	(114)	9,052	(498)
Positive	313	(98)	2,163	(587)	9,067	(1,590)	19,612	(2,445)
Total	367	(99)	2,669	(614)	12,315	(1,704)	28,664	(2,943)
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)

Notes: 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 5 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.

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-squared	0.079	0.122	0.084	0.103

Panel B. Firm Level

	3B.1	3B.2	3B.3	3B.4
Firm TFP	0.289***	0.289***	0.291***	0.296***
	(0.026)	(0.025)	(0.026)	(0.027)
Lagged firm TFP		0.019		0.024
		(0.017)		(0.014)
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***
	(0.150)	(0.126)	(0.174)	(0.158)
Sample size	42,032	42,032	42,032	42,032
Adj. R-squared	0.092	0.100	0.090	0.098

Notes: 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.

Table 4. 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 (2,397)	9,314 (488)
Positive	18,631 (3,111)	10,337 (751)	19,350 (2,363)
Total	28,664 (3,974)	28,664 (3,148)	28,664 (2,851)
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	9,250 (789)	19,162 (2,970)
Positive	19,414 (3,498)	9,502 (702)
Total	28,664 (4,287)	28,664 (3,672)
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 3 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	8,740 (818)	14,838 (1,696)	7,708 (425)	10,330 (991)	10,401 (1,291)
Positive	15,135 (2,305)	9,037 (701)	16,167 (2,279)	13,545 (1,792)	13,474 (1,745)
Total	23,875 (3,123)	23,875 (2,397)	23,875 (2,704)	23,875 (2,783)	23,875 (3,036)
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)

[Table 4 Continued]

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	8,188 (673)	14,395 (1,809)	13,387 (1,706)	7,315 (430)
Positive	15,687 (2,686)	9,480 (771)	10,488 (916)	16,560 (2,077)
Total	23,875 (3,359)	23,875 (2,580)	23,875 (2,622)	23,875 (2,507)
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)

Notes: Response coefficients are estimated for each firm. Coefficients in Panels A and B are estimated using 10-year rolling windows and firms with 5 observations or more and those in Panels C and D using for 10-year rolling windows and firms with 7 observations or more. Numbers in parentheses are the number of firms with statistically significant at the 10% level in the first three rows for each panel and the average coefficient of the firms with statistically significant at the 10% 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.