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ABSTRACT

Yes, most likely. The firm-level evidence on costly reversibility is even stronger than the prior evidence at the plant level. The firm-level investment rate distribution is highly skewed to the right, with a small fraction of negative investments, 5.79%, a tiny fraction of inactive investments, 1.46%, and a large fraction of positive investments, 92.75%. When estimated via simulated method of moments, the standard investment model explains the average value premium, while simultaneously matching the key properties of the investment rate distribution, including the cross-sectional volatility, skewness, and the fraction of negative investments. The combined effect of costly reversibility and operating leverage is the key driving force behind the model's quantitative performance.

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1 Introduction

Costly reversibility means that firms face higher costs in cutting than in expanding capital stocks. Initiated by Arrow (1968), a prominent theoretical literature on costly reversibility has long been established in both the real options framework (Bernanke 1983; McDonald and Siegel 1986; Dixit and Pindyck 1994) and the neoclassical q-theory of investment (Abel 1983; Abel and Eberly 1994, 1996). Abel et al. (1996) clarify the different but complementary interpretations as well as the mathematical equivalence of these two theories. The basic insight is that costly reversibility not only reduces negative investments but also raises the hurdle for positive investments.

In asset pricing, a large theoretical literature has studied the implications of costly reversibility on expected returns. In contemporaneous and independent work, Zhang (2005) and Cooper (2006) show that costly reversibility helps explain the average value premium in the neoclassical investment and real options models, respectively. Intuitively, value firms are burdened with more unproductive capital in bad times, finding it more difficult to downsize so as to yield more cyclical cash flows and higher expected returns than growth firms. In a related real options model, Carlson, Fisher, and Giammarino (2004) emphasize the role of operating leverage in explaining the value premium.

The quantitative importance of costly reversibility in the cross section has recently been called into question by Clementi and Palazzo (2019), who argue that upon hit by adverse shocks, U.S. public firms have "ample latitude" to divest their unproductive assets. In particular, "each quarter on average 18.2% of firms record negative gross investment (p. 282)," suggesting that "plenty of firms downsize, at all times (p. 287)," and that there exists "no sign of irreversibility (p. 289)." Clementi and Palazzo also argue that for the standard investment model to explain the average value premium, its implied investment rates must be counterfactual, with a tiny fraction of negative rates and a cross-sectional volatility that is an order of magnitude smaller than that in the data.

This paper reexamines the role of costly reversibility in U.S. public firms. In the 1962–2018 sample, which contains 175,025 firm-year observations in Compustat, we show that the firm-level investment rate distribution is highly skewed to the right, with a small fraction of negative investment rates (below -1% per annum), 5.79%, a long right tail, a skewness of 3.44, and an excess kurtosis of 15.58. The fraction of inactive investment rates (between -1% and 1%) is small, 1.46%. The asymmetry between the small fraction of negative investment rates, 5.79%, and the large fraction of positive investment rates (above 1%), 92.75%, strongly indicates costly reversibility.[1]

Surprisingly, the firm-level evidence on costly reversibility is even stronger than the prior plant-level evidence in Cooper and Haltiwanger (2006). The firm-level fraction of negative investment rates is smaller, 5.79% versus 10.4%, and the fraction of inactive investment rates is also smaller, 1.46% versus 8.1%, giving rise to a substantially larger fraction of positive investment rates, 92.75% versus 81.5%. As such, the firm-level distribution is even more asymmetric, with an even longer right tail, than the plant-level distribution. Sample criteria likely play a role. Cooper and Haltiwanger include only relatively large manufacturing firms in continuous operations throughout their 1972–1988 sample. In contrast, following standard sample criteria in empirical finance, our sample includes firms in different industries (not just manufacturing), with no restrictions on size or age.

The highly skewed firm-level investment rate distribution is robust to the exclusion of firm-year observations with large mergers and acquisitions, in which the target's assets are at least 15% of the acquirer's assets. The skewed investment rate distribution is also present in both the small-firm and big-firm samples split by the NYSE median market equity and in all ten industries.[2]

Our evidence contrasts sharply with Clementi and Palazzo's (2019). Replicating their work, we find that their evidence originates from the combination of a data error that arises from an internal inconsistency between their measures of net investment and depreciation rates, nonstandard sample criteria that curb the right tail of the investment rate distribution, and a highly questionable research practice of cutting off the right tail of the quarterly investment rate distribution at 0.2.

[1] Our definition of negative investment rates (below -1%), inactive investment rates (between -1% and 1%), and positive investment rates (above 1%) follows exactly the definition of Cooper and Haltiwanger (2006).

[2] We work with ten industries split by the Standard Industrial Classification (SIC) codes to ensure a sufficient number of firms in any given year (the minimum number is only five even with ten industries).

Quantitatively, the standard investment model explains the average value premium, while simultaneously matching the key moments of the investment rate distribution. Using Simulated Method of Moments (SMM), we estimate four parameters, including the upward and downward adjustment cost parameters, the fixed cost of production, and the conditional volatility of firm-specific productivity. We target seven data moments, including the average value premium, the cross-sectional volatility and skewness of individual stock excess returns, the cross-sectional volatility, skewness, and persistence of investment rates, as well as the fraction of negative investment rates.

The formal SMM estimation and tests strongly indicate the presence of costly reversibility and operating leverage in U.S. public firms. The downward adjustment cost parameter is estimated to be 508.2 ($t = 13.39$), which is substantially higher than the upward parameter, 0.63 ($t = 4.6$). The fixed cost of production is estimated to be 0.0637, which is more than four standard errors from zero.

The model matches the average value premium of 0.43% per month in the 1962–2018 sample, with a t-value of 1.97. For investment rates, the cross-sectional volatility is 62% per annum, which is close to 58.5% in the data, and the fraction of negative investment rates is 5.78% in the model (5.79% in the data). The test of overidentification fails to reject the standard investment model with the seven moments, with a p-value of 0.59. Comparative statics show that the combined effect of costly reversibility and operating leverage is the key driving force of the model's performance.

Costly reversibility has been embedded in a large theoretical literature in asset pricing. For example, Carlson, Fisher, and Giammarino (2006) use a real options model to explain long-term underperformance following equity issues. Gomes and Schmid (2010) show that the relation between financial leverage and expected returns depends on the investment opportunities of the firms. Tuzel (2010) shows that firms with higher real estate holdings earn higher average returns because real estate faces higher disinvestment costs and depreciates more slowly than other capital. Li (2018) incorporates shocks to the price of capital goods into the standard investment model to explain value and momentum simultaneously. Bai et al. (2019) construct a general equilibrium model with disasters to explain the failure of the unconditional CAPM in capturing the value premium. Alas, an important weakness of this theoretical literature is that the empirical foundation of costly reversibility has been largely overlooked, as evidenced by Clementi and Palazzo (2019). We fill this glaring gap. We also strengthen the econometric rigor of this applied literature by going beyond calibration to present formal tests on costly reversibility and operating leverage via SMM.

Several studies provide direct evidence on costly reversibility but only on very small samples.[3] We instead provide large-sample, albeit indirect, evidence that befits our focus on the cross section of returns. Our empirical approach at the firm level is rooted in the plant-level studies on costly reversibility (Caballero, Engel, and Haltiwanger 1995; Doms and Dunne 1998; Cooper and Haltiwanger 2006; Gourio and Kashyap 2007). These studies examine manufacturing plants from the U.S. Census Bureau's Longitudinal Research Database. Our firm-level evidence is of independent interest, as the Census Bureau stopped collecting relevant data such as capital retirements in the late 1980s. More broadly, our work is related to the corporate finance literature on the impact of costly reversibility on corporate policies.[4] We instead focus on the cross section of returns.

The rest of this paper is organized as follows. Section 2 presents detailed evidence on the firm-level investment rate distribution and explains why our evidence differs from Clementi and Palazzo's (2019). Section 3 shows that the standard investment model can explain the value premium and the key properties of the investment rate distribution simultaneously. Finally, Section 4 concludes.

[3] Pulvino (1998) shows that financially constrained airliners receive lower prices when selling used aircraft and are more likely to sell to industry outsiders than unconstrained airlines. Ramey and Shapiro (2001) use equipment-level data from aerospace plants that closed in the 1990s and estimate the average market value of equipment to be only 28 cents per dollar of replacement costs. Gavazza (2011) examines commercial aircraft markets and shows that assets with a thinner market are more costly to sell, and firms hold on longer to less productive assets.

[4] Benmelech and Bergman (2009) show that debt tranches secured by more redeployable assets have lower credit spreads, higher credit ratings, and higher loan-to-value ratios among U.S. airlines. Almeida, Campello, and Hackbarth (2011) show that assets are more likely to transfer from financially distressed to financially healthy firms when assets are more specific across industries but less specific across firms within an industry. Ortiz-Molina and Phillips (2014) show that firms with less reversible assets have higher accounting-based implied costs of equity than firms with more reversible assets. Kim and Kung (2017) construct a costly reversibility score at the asset level and show that firms with less reversible capital are more cautious about investment under uncertainty.

2 Evidence on the Firm-level Investment Rate Distribution

Data on monthly stock returns are from Center for Research in Security Prices (CRSP) monthly stock files and data on firm-level accounting variables from annual Standard and Poor's Compustat industrial files. We exclude financial firms (SIC codes between 6,000 and 6,999), firms with negative book equity, and firm-year observations with nonpositive total assets, net property, plant, and equipment, or sales. The sample is annual, spanning from 1962 to 2018.

2.1 Measuring Investment Rates

In the standard investment model (Section 3.1), period-t stock variables are measured at the beginning of period t, and period-t flow variables are over the course of period t. In contrast, in Compustat, both stock and flow variables are recorded at the end of period t. As such, when working with annual data, for the year $t = 2002$, for instance, we take period-t stock variables from the 2001 balance sheet and period-t flow variables from the 2002 income or cash flow statement.

We measure gross investment rates as in Goncalves, Xue, and Zhang (2019). Capital stock, denoted K_{it}, is net property, plant, and equipment (net PPE, Compustat annual item PPENT). Many studies use gross PPE as capital stock. However, in financial accounting, gross PPE is the accumulated historical cost of investments, and net PPE is gross PPE minus accumulated depreciation. Net PPE is part of a firm's total assets, but gross PPE is not. Because the accumulated depreciation is not part of the existing assets, net PPE is a more appropriate measure of capital than gross PPE.

More precisely, let δ_{it} be the depreciation rate and I_{it} be investment. Capital stock accumulates as $K_{is+1} = (1 - \delta_{is})K_{is} + I_{is}$, for $s = 0, 1, \ldots, t-1$, in which year 0 is the year when firm i first appears in Compustat. Recursively substituting K_{is} yields:

$$K_{it} = \left(K_{i0} + \sum_{s=0}^{t-1} I_{is} \right) - \sum_{s=0}^{t-1} \delta_{is} K_{is}. \tag{1}$$

In equation (1), $K_{i0} + \sum_{s=0}^{t-1} I_{is}$ is accumulated historical investments (gross PPE), and $\sum_{s=0}^{t-1} \delta_{is} K_{is}$ is accumulated depreciation expenses. As such, K_{it} is net PPE. Hulten (1991, p. 126) also argues that net capital stock is consistent with the production function, and the gross stock is consistent only in the unlikely scenario in which assets retain full efficiency until collapsing completely.

We measure the depreciation rate, δ_{it}, as the amount of depreciation and amortization (Compustat annual item DP) minus the amortization of intangibles (item AM, zero if missing), scaled by net PPE (item PPENT). We measure investment, I_{it}, as $K_{it+1} - (1 - \delta_{it})K_{it}$. Equivalently, the gross investment rate, I_{it}/K_{it}, is the net investment rate, $(K_{it+1} - K_{it})/K_{it}$, plus the depreciation rate, δ_{it}. An advantage of this gross investment rate measure is that the capital accumulation equation, $K_{it+1} = I_{it} + (1 - \delta_{it})K_{it}$, is automatically satisfied across firms and over time.

In contrast, measuring investment as capital expenditures (Compustat annual item CAPX) minus sales of PPE (item SPPE, zero if missing) violates the capital accumulation equation frequently in the data (Goncalves, Xue, and Zhang 2019). In the 1962–2018 sample, this alternative investment measure deviates from $K_{it+1} - (1 - \delta_{it})K_{it}$ by more than 10.28%, 33.3%, and 60.13% of net PPE in magnitude for 25%, 10%, and 5% of the firm-year observations. The sample coverage of item SPPE is only 71.82% in the 1962–2018 sample and 76.78% from 1971 onward. Even from 1971 onward, CAPX − SPPE still deviates from $K_{it+1} - (1 - \delta_{it})K_{it}$ by more than 10.53%, 34.13%, and 61.36% of net PPE for 25%, 10%, and 5% of the firm-year observations.

In addition, item SPPE understates the frequency and magnitude of negative investments. SPPE only records cash proceeds from sales of PPE, but not equity or debt proceeds or disposition via asset exchanges. For example, Slovin, Sushka, and Polanchek (2005) examine equity-based asset sales. Even for cash-based sales, SPPE records book value reductions (negative investments) plus gains or losses. Because losses are more likely, SPPE tends to understate negative investments.

We should emphasize that our investment measure, $K_{it+1} - (1 - \delta_{it})K_{it}$, likely overstates the frequency of negative investment rates. Net PPE can decrease not only from capital retirements and sales of PPE, but also from restructuring charges, impairment losses, and foreign currency translations, all of which do not involve actual disinvestments (Wahlen, Baginski, and Bradshaw 2018, chapter 8). In particular, U.S. Generally Accepted Accounting Principles require that the values of long-lived assets must be reevaluated periodically for impairments and written down in the presence of impairment losses. However, asset values are not allowed to adjust upward in reevaluation.

Finally, our investment measure accounts for mergers and acquisitions (M&As), but the alternative measure as CAPX minus SPPE does not. M&As are prevalent. Goncalves, Xue, and Zhang (2019) show that firm-year observations with M&As of any size account for close to 40% of the Compustat sample. More important, M&As are not random events. Firms with M&As are more likely to be high market-to-book, high investment, high profitability, and high momentum firms than firms without M&As. As such, including these observations is crucial for asset pricing purposes.

2.2 The Cross-sectional Distribution of Gross Investment Rates

Panel A of Table 1 reports the cross-sectional moments of gross investment rates in the 1962–2018 sample, which contains in total 175,025 firm-year observations. For each fiscal year we winsorize the firm-level gross investment rates at the 1%–99% level. The average investment rate is 38.4% per annum, which is substantially higher than the median of 22.4%. The cross-sectional standard deviation of the investment rates is large, 58.5%. The skewness coefficient is 3.44, and excess kurtosis (relative to that of the normal distribution) 15.58. The first-order autocorrelation estimated from cross-sectional regressions of investment rates on lagged investment rates is 25.5%.

As noted, following Cooper and Haltiwanger (2006), we define the investment rates between -1% and 1% as inactive, those below -1% as negative, and those above 1% as positive, investment rates. The fraction of negative investment rates is small, only 5.79%, and the fraction of inactive rates is tiny, only 1.46%. Most important, the asymmetry between the fractions of negative and positive investment rates, 5.79% versus 92.75%, strongly indicates costly reversibility in U.S. public firms. Panel A of Figure 1 shows the histogram of the pooled firm-year observations of gross investment rates. The firm-level distribution is highly skewed, with a long right tail, and also leptokurtic.

Panel B of Table 1 reports the properties of an alternative investment rate, in which investment is CAPX minus SPPE.[5] The alternative measure understates the fraction of negative investment rates to only 2.03%, in contrast to 5.79% for the benchmark measure. The mean, standard deviation, skewness, and excess kurtosis are 31.5%, 37.5%, 3.05, and 12.17, respectively, all of which are lower than those of the benchmark investment rates in Panel A. The alternative measure also overstates the persistence of the investment rates to 39%. Finally, Panel A of Figure A1 in Appendix A reports the histogram of the alternative investment rates. Clearly, the left tail with negative investment rates is substantially thinner than that in Panel A of Figure 1. The right tail is also thinner.

2.2.1 Comparison with the Prior Plant-level Evidence

It is informative to compare the properties of the firm-level gross investment rates with those of the plant-level investment rates reported in Cooper and Haltiwanger (2006). Cooper and Haltiwanger use a balanced panel with about 7,000 large, manufacturing plants in continuous operation between 1972 and 1988 from the U.S. Census Bureau's Longitudinal Research Database collected via its Annual Survey of Manufacturers. Their sample ends in 1988 because the Census Bureau stopped collecting data on gross capital retirements in 1987 and the book value of capital in 1989.

Cooper and Haltiwanger (2006) document several stylized facts of the plant-level investment rate. First, about 8.1% of the plant-year observations have inactive investment rates. Second, the investment rate distribution is asymmetric with about 10.4% negative, 8.1% inactive, and 81.5% positive investment rates. Finally, the serial correlation of investment rates is only 5.8%.

Comparing the firm-level evidence in Table 1 to the plant-level evidence, we observe that firm-level investment rates have an even lower fraction of negative investment rates, 5.79% versus 10.4%. The inactive fraction is also much smaller at the firm level, 1.46% versus 8.1%. As such, firm-level investment rates are even more asymmetric, with an even longer right tail, than plant-level investment rates. In all, surprisingly, the asymmetry evidence indicates even stronger costly reversibility at the firm level than at the plant level. However, perhaps not surprisingly, the evidence on lumpy invest-

[5]Because item CAPX is available for 98.15% of the observations (we set missing SPPE to zero), the total number of firm-year observations in Panel B is 171,787, which is smaller than 175,025 in Table 1.

ment is weaker at the firm level, as indicated by the smaller inactive region. In addition, investment rates are more persistent at the firm level, with a higher autocorrelation, 25.5% versus 5.8%.

Panel B of Figure 1 is cut-and-pasted from Cooper and Haltiwanger's (2006) Figure 1 on the histogram of plant-level investment rates in their sample. A comparison with Panel A, which plots the firm-level investment rate distribution in our Compustat sample, shows that the firm-level distribution is much more dispersed and more asymmetric with a longer right tail. In particular, the firm-level distribution varies from -0.5 to 2.5, whereas the plant-level distribution only from -0.2 to 0.8.

Sample criteria most likely play an important role in explaining the differences. Befitting their economic question, Cooper and Haltiwanger (2006) include only relatively large manusfacturing plants, which are in continuous operations throughout their sample period. In contrast, following the standard sample criteria in empirical asset pricing, our Compustat sample includes firms in different industries (not just manufacturing), with no restrictions on size or age. As such, the firms in our sample are substantially more heterogeneous than Cooper and Haltiwanger's plants, giving rise to a more dispersed cross-sectional distribution of gross investment rates.

Aggregation from plants to firms is also important for some of the differences between our firm-level evidence and Cooper and Haltiwanger's (2006) plant-level evidence. In particular, negative investments by some plants can be offset by positive investments by other plants within the same firm. This within-firm aggregation most likely gives rise to a smaller fraction of negative investments at the firm level than at the plant level, 5.8% versus 10.4%, a smaller fraction of inactive investments, 1.46% versus 8.1%, but a higher autocorrelation of investment rates, 25.5% versus 5.8%.

A closely related issue is aggregation across heterogenous capital goods. While the standard investment model features homogenous capital for simplicity, firms in the data use heterogeneous capital goods. The capital composition can vary greatly across firms, especially those in different industries in our Compustat sample. Buying a few laptops gets lumped into an increase in net PPE in the same way as constructing a new building. This capital heterogeneity is at least partially responsible for the smaller fraction of inactive investment rates at the firm level, 1.46% versus 8.1%. Even at the plant level, Cooper and Haltiwanger (2006) emphasize that because of capital heterogeneity, the observed inactive investment rate is not informative about adjustment cost parameters.

2.2.2 Robustness

Our evidence on the highly skewed firm-level investment rate distribution is robust to the exclusion of large M&As and is also present in both small and big firms and within different industries.

The Impact of Large M&As Large M&As do not materially affect the asymmetry evidence. From our 1962–2018 sample, we further exclude firm-year observations with large M&As, in which the target's book assets are at least 15% of the acquirer's book assets. The 15% cutoff has been adopted in the prior investment literature to focus on organic growth (Whited 1992). To identify M&As in a given fiscal year, we take the maximum of acquisitions (Compustat annual item AQC) and the total value of acquisitions from the Securities Data Company (SDC) dataset (zero if missing in both databases). The AQC coverage starts in 1971, and the SDC coverage in 1978. Imposing the large-M&A screen removes only about 5.9% of firm-year observations from the original sample.

Table A1 in Appendix A shows that the impact of large M&As is quantitatively small. The average investment rate falls somewhat to 34.7% and the cross-sectional standard deviation to 52.7%. The median drops only slightly to 21.2%. However, the skewness increases slightly to 3.68, and the excess kurtosis to 18.88. The first-order autocorrelation of investment rates remains largely unchanged at 26.6%. The fraction of negative investment rates rises slightly to 6.03%, and the inactive investment rates to 1.53%. Finally, the histogram of the firm-level investment rates in the no-large-M&A sample in Panel B of Figure A1 is largely similar to Panel A of Figure 1.

Firm Size The highly skewed investment rate distribution is present in both small and big firms. For each fiscal year, we split the full sample in Table 1 into two subsamples, small and big, based on the NYSE median of the beginning-of-fiscal year market equity. From 1962 to 2018, the small-firm sample has in total 134,937 firm-year observations, and the big-firm sample 37,936.

Table A2 shows the cross-sectional moments of the gross investment rates, and Figure A2 shows the histograms of the firm-level investment rate distribution on the two subsamples. Although the median investment rates are close, 23% versus 21%, the average investment rate is higher in small firms than that in big firms, 40.3% versus 30.7%, and the cross-sectional standard deviation is also higher in small firms, 61.6% versus 39.2% per annum. Probably because of aggregation over more plants and over more heterogeneous capital goods, big firms have a higher autocorrelation of investment rates, 38% versus 23.6%, but a lower fraction of negative investment rates, 3% versus 6.6%, and a lower fraction of inactive investment rates, 0.7% versus 1.7%, than small firms. Although small firms have a higher cross-sectional dispersion, big firms have higher skewness, 4.4 versus 3.21, and higher excess kurtosis, 32.57 versus 13.45, than small firms.

Industries The highly skewed investment rate distribution is ubiquitous across different industries. To ensure a sufficient number of firms within each industry, we work with the Fama-French (1997) 10-industry definition.[6] Appendix A contains the detailed classifications.

Table A3 reports the cross-sectional moments of gross investment rates for each industry. Manufacturing is the largest industry, with 34,298 observations, followed by high tech, with 33,251 observations. Telecommunication is the smallest, with 3,937 observations. The average investment rate ranges from 14% in utilities to 51.3% in high tech, and the median from 11% to 32.8%. The cross-sectional standard deviation varies from 19.7% in utilities to 65.9% in health care.

More important, the investment rate distributions are all right skewed, with the skewness coefficient varying from 2.76 in telecommunication to 4.39 in manufacturing. The investment rate distributions are also all leptokurtic, with the excess kurtosis ranging from 10.3 in health care to 33.8 in utilities. The investment rates are least persistent in manufacturing, with a first-order autocorrelation of 17.8%, and are most persistent in utilities, with an autocorrelation of 32.4%. The fraction

[6] Telecommunication has the lowest average number of firms each year, 69, and its annual minimum is only five.

of negative investment rates is the lowest in utilities, 2.94%, and the highest in energy, 9.68%. The fraction of inactive investment rates is small, ranging from 0.78% in utilities to 2.35% in "Other."

Figure A3 reports the histogram of the firm-level investment rate distribution for each industry. The histograms are all largely similar to the histogram of the full sample in Panel A of Figure 1. The only exception is the utilities industry, which, despite its long right tail, has most of its probability mass concentrated around its median, giving rise to an extremely high excess kurtosis of 33.8. This feature likely reflects the regulated nature of this industry, which limits competition.

2.3 Replicating Clementi and Palazzo (2019)

Our evidence contrasts sharply with that in Clementi and Palazzo (2019), who report no sign of costly reversibility in U.S. public firms. In this subsection, we show that their evidence is misleading, originating from (i) a data error that arises from the internal inconsistency between their measures of net investment and depreciation rates; (ii) nonstandard sample criteria that restrict the right tail of the firm-level investment rate distribution; and (iii) a highly questionable research practice of cutting off the long right tail of the investment rate distribution at 0.2.

Panel A of Figure 2 is cut-and-pasted from Clementi and Palazzo's (2019) Figure 1, which reports the cross-sectional distribution of the quarterly gross investment rates in their 1978–2016 sample. The distribution is largely symmetric, with a large fraction, 18.2%, of negative investment rates (below -1%). The symmetric distribution and the large fraction of negative investment rates seem to indicate a severe lack of costly reversibility in U.S. public firms. As noted, a long right tail of the investment rate distribution is the telltale sign of costly reversibility (Cooper and Haltiwanger 2006).

Interestingly, at the conceptual level, Clementi and Palazzo's (2019) investment rate measure is virtually identical to ours, which is in turn from Goncalves, Xue, and Zhang (2019). Clementi and Palazzo (p. 286) measure the investment rate as $(\text{PPENTQ}_{it} - \text{PPENTQ}_{it-1})/\text{PPENTQ}_{it-1} + \delta_i$, in which PPENTQ is net PPE (Compustat quarterly item PPENTQ), and δ_i the depreciation rate. Their investment rate measure is identical to ours in two crucial aspects: (i) Capital is measured as net PPE; and (ii) the change in net PPE is net investment, which automatically accounts for M&As.

For replication, we work with quarterly data in the same 1978–2016 span. We exclude financials, firms with negative book equity, and firm-quarter observations with nonpositive total assets, net PPE, or sales. Our replication sample contains in total 463,426 firm-quarter observations. Capital is net PPE (Compustat quarterly item PPENTQ). The depreciation rate, δ_{it}, is the amount of depreciation and amortization (item DPQ) minus the amortization of intangibles (Compustat annual item AM divided by four, zero if missing, as the quarterly equivalent of item AM is not available), scaled by net PPE. The linear interpolation works because most U.S. firms use the straight-line depreciation method for financial reporting purposes (Wahlen, Baginski, and Bradshaw 2018, p. 506). The quarterly gross investment rate, I_{it}/K_{it}, is the net investment rate, $(K_{it+1} - K_{it})/K_{it}$, plus the depreciation rate, δ_{it}. For the pooled firm-quarter observations of the fiscal quarters ending in a given fiscal quarter, we winsorize gross investment rates at the 1%–99% level.

Our replication in Panel B of Figure 2 clearly shows a highly skewed pattern with a long right tail in quarterly gross investment rates. The fraction of negative investment rates is only 5.96%, which is substantially lower than 18.2% in Clementi and Palazzo's (2019) Table I. Following Cooper and Haltiwanger (2006), Clementi and Palazzo treat the investment rates between -1% and 1% as inactive, and the investment rates below -1% as negative investment rates (despite the difference in annual versus quarterly frequency). To facilitate comparison, we adopt the same definition.

2.3.1 Different Depreciation Rates

In what follows, we carefully trace the sources of the differences between Clementi and Palazzo's (2019) Figure 1 and our replication in Panel B of Figure 2. The most important source is the measurement of the depreciation rate, δ_{it}. We calculate δ_{it} directly from the firm-level data on depreciation and amortization expenses in Compustat. In contrast, Clementi and Palazzo measure δ_{it} as the average industry-level geometric depreciation rates from Bureau of Economic Analysis (BEA).

The Clementi-Palazzo investment rate measure is flawed. Net PPE and the depreciation rate in the gross investment rate are *not* independent of each other. The accounting depreciation rates in Compustat (not BEA's depreciation rates) are embedded in net PPE via perpetual inventory method, which implements the capital accumulation equation. As noted, most U.S. firms use the straight-line depreciation method for financial reporting purposes. In contrast, BEA estimate geometric depreciation rates (Hulten and Wykoff 1981; Fraumeni 1997). As such, the Clementi-Palazzo investment rate violates the capital accumulation equation for every period and for every firm.

The accounting depreciation rates are on average higher than the BEA depreciation rates, 5.86% versus 2.4% per quarter, in the 1978–2016 sample. (The data on the BEA's average industry-level depreciation rates used in Clementi and Palazzo (2019) are obtained from Berardino Palazzo.) By adding lower BEA depreciation rates to net PPE's net growth rates, which embed higher accounting depreciation rates, Clementi and Palazzo erroneously shift the whole firm-level gross investment rate distribution leftward, giving rise to a higher fraction of negative investment rates. This data error paints a misleading picture of a lack of costly reversibility in U.S. public firms.

Panel A of Figure 3 reports the histogram of the quarterly BEA average industry-level depreciation rates assigned to the firm level based on the SIC or NAICS codes per Clementi and Palazzo (2019). The BEA depreciation rates are computed across the 2- or 3-digit NAICS industries. Prior to June 1985, when NAICS codes become available, we use SIC codes and convert them into NAICS codes using the mapping tables from the Census Bureau. For comparison, Panel B reports the histogram of the quarterly Compustat firm-level depreciation rates. The cross-sectional distribution of the BEA depreciation rates is largely symmetric, ranging from 0.01 to 0.05. In contrast, the cross-sectional distribution of the Compustat depreciation rates is much more dispersed, ranging from 0.00 to more than 0.35, and more important, highly skewed with a a long right tail.

2.3.2 Different Sample Criteria

Still, we cannot replicate Clementi and Palazzo's (2019) Figure 1, even after tracing their steps to erroneously combine BEA's industry-level depreciation rates with Compustat's net growth rates of net PPE to measure gross investment rates. From Panel A of Figure 4, the firm-level investment rate distribution measured in this way is still skewed, with a long right tail, in our replication sample. Clementi and Palazzo's Table I reports an average investment rate of 3.5% per quarter, which is close to the median of 3.06% in our sample. Because of the long right tail, the mean investment rate with the BEA depreciation rates in our sample is 5.82%. From the left tail, the fraction of negative investment rates is 15.73% in our sample, which is not far from 18.2% in their Table I.

We next ask whether the different sample criteria can explain why Panel A of Figure 4 with the BEA depreciation rates still shows a long right tail. We find that imposing the same sampling criteria as in Clementi and Palazzo (2019) helps match their mean and standard deviation of the investment rates almost exactly but still fails to explain the missing right tail in their Figure 1.

Our replication sample contains 463,426 firm-quarter observations, in contrast to Clementi and Palazzo's (2019) 296,218. The crux is that we adopt sample criteria that are more standard in empirical finance. In contrast, Clementi and Palazzo impose substantially more stringent sample criteria: (i) Excluding financial firms, utilities, and unclassified firms (SIC codes $\geq$ 9000); (ii) dropping firms with fewer than 12 past quarterly investment rates (i.e., dropping the first 12 quarterly investment rate observations); (iii) dropping firm-quarter observations associated with acquisitions larger than 5% of total assets; (iv) discarding firm-quarter observations in the top and bottom 0.5% of the pooled distribution of quarterly investment rates; and (v) dropping firm-quarter observations with missing values of investment rates or book-to-market. In particular, criterion (ii) and (iii) largely explain the substantial differences between our replication sample and their original sample.

We construct a reproduction sample by imposing exactly their more stringent criteria. Our reproduction sample contains 295,155 firm-quarter observations (close to 296,218 in their original sample). The average investment rate in our reproduction sample is 3.51% per quarter, which is close to 3.5% reported in their Table I. The standard deviation of the investment rate is 9.27% in our reproduction sample, which is close to 9.5% in their Table I. Finally, the fraction of negative investment rates in our reproduction sample is 17.8%, which is also close to 18.2% in their Table I. As such, our reproduction sample is fairly close to Clementi and Palazzo's (2019) original sample. However, Panel B of Figure 4 shows that our reproduction sample continues to exhibit a long right tail for the firm-level distribution of investment rates measured with the BEA depreciation rates.

2.3.3 The Missing Right Tail

The differences between Panel B of Figure 4, which is a direct reproduction of Clementi and Palazzo's (2019) Figure 1, and their original Figure 1 raise a disconcerting question. The only way we can fully reproduce their Figure 1 is to cut off the right tail of the firm-level investment rate distribution at 0.2. Nowhere in their paper do Clementi and Palazzo admit that such a problematic procedure has been performed. However, their original Figure 1 displays a probability mass at 0.2 that is clearly higher and thicker than the mass at -0.2. Because Clementi and Palazzo conclude "no sign of irreversibility (p. 289)," yet a long right tail of the investment rate distribution is the "smoking gun" evidence in support of costly reversibility (Cooper and Haltiwanger 2006), cutting off the right tail is, at a minimum, a highly questionable research practice (Simmons, Nelson, and Simonsohn 2011).[7]

3 Matching Moments

In this section, we show that the standard investment model can explain the average value premium, while simultaneously matching the key properties of the investment rate distribution (properly documented). Section 3.1 describes the model, and Section 3.2 shows the model's performance.

3.1 The Standard Investment Model

We adopt a simplified setup of Zhang (2005) and Bai et al. (2019). The production function is:

$$\Pi_{it} \equiv \Pi(K_{it}, Z_{it}, X_t) = X_t Z_{it} K_{it}^{\alpha} - f, \tag{2}$$

[7] After we fail to reproduce their Figure 1 with Panel B of Figure 4, we request and obtain the codes and data from Clementi and Palazzo. The following segment of their Stata codes implemented the problematic procedure: "gen hist = inv_rate," "replace hist = . if hist > 0.2," and "replace hist = . if hist < −0.2."

in which Π_{it} is firm i's operating profits, K_{it} capital, X_t the aggregate productivity, Z_{it} firm-specific productivity, $\alpha \in (0, 1)$ the curvature parameter, and $f > 0$ the fixed cost of production.

The aggregate productivity, X_t, has a stationary Markov transition function:

$$x_{t+1} = \overline{x}(1 - \rho_x) + \rho_x x_t + \sigma_x \epsilon^x_{t+1}, \tag{3}$$

in which $x_t \equiv \log X_t$, and ϵ^x_{t+1} is an independently and identically distributed (i.i.d.) standard normal shock. The firm-specific productivity for firm i, Z_{it}, has a transition function given by:

$$z_{it+1} = \rho_z z_{it} + \sigma_z \epsilon^z_{it+1}, \tag{4}$$

in which $z_{it+1} \equiv \log Z_{it+1}$, and ϵ^z_{it+1} is an i.i.d. standard normal shock. Finally, ϵ^z_{it+1} and ϵ^z_{jt+1} are uncorrelated for any $i \neq j$, and ϵ^x_{t+1} and ϵ^z_{it+1} are uncorrelated for any i.

Let I_{it} denote firm i's investment over period t. Capital accumulates as follows:

$$K_{it+1} = I_{it} + (1 - \delta)K_{it}, \tag{5}$$

in which $\delta \in (0, 1)$ is the depreciation rate. Investment entails asymmetric adjustment costs:

$$H(I_{it}, K_{it}) = \frac{\theta_t}{2}\left(\frac{I_{it}}{K_{it}}\right)^2 K_{it} \tag{6}$$

in which $\theta_t \equiv \theta^+ \times \mathbf{1}_{\{I_{it} \geq 0\}} + \theta^- \times \mathbf{1}_{\{I_{it} < 0\}}$, $\mathbf{1}_{\{\cdot\}}$ is the indicator function that equals one if the event in $\{\cdot\}$ is true and zero otherwise, and $\theta^- > \theta^+ > 0$ are constant parameters (Zhang 2005).

The stochastic discount factor, denoted M_{t+1}, is specified exogenously as:

$$M_{t+1} = \beta e^{[\gamma_0 + \gamma_1(x_t - \overline{x})](x_t - x_{t+1})}, \tag{7}$$

in which $\beta \in (0, 1)$ is the time discount factor, and $\gamma_0 > 0$ and $\gamma_1 < 0$ are constant parameters.

After observing X_t and Z_{it}, firm i makes optimal investment decision, I_{it}, and optimal exit decision, χ_{it}, to maximize its cum-dividend market equity, denoted V_{it}, given by:

$$V(K_{it}, X_t, Z_{it}) = \max_{\{\chi_{it}\}} \left(\max_{\{I_{it}\}} \Pi_{it} - I_{it} - H(I_{it}, K_{it}) + E_t\left[M_{t+1}V(K_{it+1}, X_{t+1}, Z_{it+1})\right], 0 \right). \quad (8)$$

When the inner maximand is greater than or equal to zero, firm i stays in the economy, i.e., $\chi_{it} = 0$. Evaluating the value function at the optimum yields $V_{it} = D_{it} + E_t[M_{t+1}V_{it+1}]$, in which $D_{it} \equiv \Pi_{it} - I_{it} - H(I_{it}, K_{it})$, and $E_t[M_{t+1}r^S_{it+1}] = 1$, in which $r^S_{it+1} \equiv V_{it+1}/(V_{it} - D_{it})$ is the stock return.

When the inner maximand is negative, firm i exits at the beginning of period t, i.e., $\chi_{it} = 1$. We set its stock return over period $t-1$, r^S_{it}, to be a predetermined delisting return, denoted $\widetilde{R}$. The exit firm enters an immediate reorganization process. The current shareholders receive nothing and leave. New shareholders take over the firm's capital to form a new firm. For tractability, we assume that the reorganization process occurs instantaneously. At the beginning of period t, the exit firm is replaced by a new firm with a new firm-specific log productivity of $\bar{z}$, which is its unconditional mean. This simple modeling of entry and exit keeps the number of firms constant (Bai et al. 2019).

3.2 Structural Estimation

We first discuss predetermined parameters and then describe the simulation-based estimation for the remaining key parameters. Next, we show that the standard investment model can explain the average value premium, while simultaneously matching the key moments of the firm-level investment rate distribution. Finally, we conduct comparative statics to illustrate the model's mechanisms.

3.2.1 Predetermined Parameters

Despite its simplicity, the standard investment model still has in total 14 parameters, $\{\beta$, γ_0, γ_1, α, $\overline{x}$, ρ_x, σ_x, δ, $\widetilde{R}$, ρ_z, σ_z, f, c^+, $c^-\}$ due to its fully specified nature. We calibrate a set of predetermined parameters but estimate the key parameters via SMM. We work in monthly frequency.

Our strategy for predetermined parameters largely follows prior studies. First, we use prior estimates and conventional values to pin down eight parameters. Because these parameters are determined tightly, we have essentially no degrees of freedom in picking their values. The three parameters in the pricing kernel, β, γ_0, and γ_1, are pinned down by three aggregate asset pricing moments. As in Lin and Zhang (2013), we set $\beta = 0.9999$, $\gamma_0 = 17$, and $\gamma_1 = -1,000$, which yield an average Sharpe ratio of 0.37 per annum, an average interest rate of 2.63%, and an interest rate volatility of 2%. We set the persistence of aggregate productivity, ρ_x, to $0.95^{1/3} = 0.983$ and its conditional volatility, $\sigma_x = 0.007/\sqrt{1 + \rho_x^2 + \rho_x^4} = 0.0041$, matching the quarterly values of 0.95 and 0.007, respectively, in Cooley and Prescott (1995). We set the curvature parameter, α, to 0.7, which is close to the estimates in Hennessy and Whited (2007). Finally, Hou, Xue, and Zhang (2018) estimate the average (performance-related) delisting return in CRSP to be -12.33%, to which we set $\widetilde{R}$.

In our 1962–2018 sample, the depreciation rates vary over time and across firms. The mean is 20.71% per annum, the median 15.95%, and the cross-sectional volatility 16.54%. The distribution is also right skewed, with a skewness of 2.02, and leptokurtic, with an excess kurtosis of 6.23 (untabulated). In the model, the depreciation rate, δ, is constant. We take a conservative approach to set δ to be 0.2/12 per month, which is close to the average annual rate. Modeling stochastic depreciation rates with an empirically plausible distribution likely only strengthens the model's ability to explain the key properties of the investment rate distribution (volatility and skewness).

Second, three parameters are important for our quantitative results but are unobservable with little empirical guidance. In particular, as the only source of firm heterogeneity in the standard investment model, firm-specific productivity shocks should be interpreted as an stand-in for different firm-specific shocks underlying cross-sectional heterogeneity in the data. The persistence, ρ_z, and conditional volatility, σ_z, of firm-specific productivity, z_{it}, affect the cross-sectional dispersion (driven by the unconditional standard deviation of z_{it}) in a quantitatively similar way. We fix ρ_z at 0.97 as in prior studies (Zhang 2005) but estimate σ_z to match the cross-sectional return volatility.

Finally, as a scaling parameter, the long-run mean of aggregate productivity, $\overline{x}$, pins down the long-term average capital in the economy. Prior studies calibrate $\overline{x}$ to set the average capital to be around one. However, doing so gives rise to too many tiny firms with very low capital stocks, which in turn have an excessive impact on the cross-sectional investment rate volatility. As such, we fix $\overline{x} = -3.18$ to set the average capital to above ten to yield a more reliable investment rate distribution.

3.2.2 Simulated Method of Moments

We are left with four key parameters, including the conditional volatility of firm-specific productivity (σ_z), the fixed cost of production (f), and the upward (θ^+) and downward (θ^-) adjustment cost parameters. Because these key parameters play an important role in driving the cross-sectional properties of investment rates and stock returns in the model, we opt to estimate them via SMM.

Table 2 reports the cross-sectional moments of stock excess returns in the data. In the January 1962–December 2018 sample, the value premium (defined as the returns of the high book-to-market decile minus the returns of the low book-to-market decile) is on average 0.43% per month ($t = 2.28$). For annual excess returns of individual stocks, the time series average of the cross-sectional standard deviation is 54.26% per annum. Consistent with Bessembinder (2018), Table 2 also reports positive time series averages of the cross-sectional skewness of individual stock excess returns, with coefficients of 0.66, 1.38, and 2.32 across monthly, annual, and 5-year horizons, respectively.

We estimate the four parameters, $\mathbf{c} \equiv (\sigma_z, f, \theta^+, \theta^-)$, to match a vector of seven data moments, denoted $\mathbf{\Psi_d}$, including four annual investment rate moments (the cross-sectional volatility, 58.48%; skewness, 3.44; autocorrelation, 25.46%; and the fraction of negative investment rates, 5.79%) from Table 1 and three return moments (the average value premium, 0.43% per month; and the cross-sectional volatility, 54.26%, and skewness, 1.38, of annual stock excess returns) from Table 2.

For a given profile of parameter values, we solve the value maximization problem in equation (8) and obtain optimal decision rules via the standard technique of value function iteration on discrete state space. Appendix B details the algorithm. We then simulate $S = 500$ artificial panels of size $(N, T + b)$, in which $N = 5,000$ is the number of firms in the cross section, $T = 57 \times 12 = 684$ the time length in the number of months, and $b = 300$ the initial time length to be discarded to reach the model's ergodic distribution. The sample length, T, matches the 1962–2018 sample (57 years).

On the simulated panels, we compute the targeted moments, denoted $\mathbf{\Psi_m(c)}$, which depends on the parameters, $\mathbf{c}$, nonlinearly. On each panel, we implement the exactly same procedures in Tables 1 and 2 that we use to compute the data moments, $\mathbf{\Psi_d}$. To calculate the value premium, we identify book equity as capital, K_{it}, in the model and the market equity as the ex dividend market value, $V_{it} - D_{it}$. The model is simulated at monthly frequency, but the investment rates in Table 1 are annual. We time-aggregate simulated monthly investments to annual by summing up 12 monthly observations within a given year and calculate the year's annual investment rate as the annual investment over the beginning-of-year capital. The model moments are averaged across the S simulations.

The point estimate, $\widehat{\mathbf{c}}$, minimizes a weighted distance between the data and model moments:

$$\widehat{\mathbf{c}} \quad = \quad \operatorname{argmin} \quad [\mathbf{\Psi_d} - \mathbf{\Psi_m(c)}]' \, \mathbf{W} \, [\mathbf{\Psi_d} - \mathbf{\Psi_m(c)}] \, , \tag{9}$$

in which $\mathbf{W}$ is the weighting matrix. Following Bloom et al. (2018), we set the diagonal elements of $\mathbf{W}$ to be $(1/\mathbf{\Psi_d})^2$ and the off-diagonal elements of $\mathbf{W}$ to be zero. With this weighting matrix, the SMM estimator in equation (9) minimizes the sum of squared percentage deviations of the model moments from the corresponding data moments. Intuitively, on econometric grounds, this weighting matrix formalizes the typical calibration practice, which assigns roughly equal weights to the targeted moments. Taking the percentage deviations makes the moments with different units comparable. This weighting matrix is analogous to the identity weighting matrix in asset pricing tests, in which all the moments in terms of average returns have the same unit (Cochrane 1996).[8]

Let $\mathbf{D} \equiv \partial \mathbf{\Psi_m(c)}/\partial \mathbf{c}$ and $\mathbf{\Gamma}$ be a consistent estimate of T times the variance-covariance matrix of the data moments, $\mathbf{\Psi_d}$, in which we account for serial correlations of up to ten lags. The estimate of $\mathbf{c}$, denoted $\hat{\mathbf{c}}$, is asymptotically normal with the variance-covariance matrix given by $\text{Cov}(\hat{\mathbf{c}}) = (1 + 1/S)(\mathbf{D'WD})^{-1}\mathbf{D'W\Gamma WD}(\mathbf{D'WD})^{-1}/T$, in which $(1 + 1/S)$ accounts for

[8]We have also explored the optimal weighting matrix (as the inverse of the variance-covariance matrix of the data moments). However, this weighting matrix assigns only a small weight to the value premium, which is a noisy series of returns. Because the average value premium is our primary focus, we opt not to use the optimal weighting matrix.

the sample variation of simulations (Lee and Ingram 1991). To construct the standard errors for the errors of individual moments, $\mathbf{\Delta} \equiv \mathbf{\Psi_d} - \mathbf{\Psi_m}$, we use the variance-covariance matrix, $\mathrm{Cov}(\mathbf{\Delta}) = (1+1/S)\left[\mathbf{I} - \mathbf{D}(\mathbf{D}'\mathbf{W}\mathbf{D})^{-1}\mathbf{D}'\mathbf{W}\right]\mathbf{\Gamma}\left[\mathbf{I} - \mathbf{D}(\mathbf{D}'\mathbf{W}\mathbf{D})^{-1}\mathbf{D}'\mathbf{W}\right]'/T$. Finally, we form a χ^2 test on the null hypothesis that all the model errors are jointly zero, $\mathbf{\Delta}'\left[\mathrm{Cov}(\mathbf{\Delta})\right]^{+}\mathbf{\Delta} \sim \chi^2$, in which χ^2 is the chi-square distribution with the degrees of freedom given by the number of moments minus that of parameters, and the superscript $^{+}$ is pseudo-inversion (Hansen 1982).

While searching over the parameter space of $\widehat{\mathbf{c}}$ to solve the optimization in equation (9), we hold the random shocks underlying the S artificial panels fixed. A new set of random shocks would give rise to a new value for the objective function even if $\widehat{\mathbf{c}}$ does not change, violating the continuity assumption of the objective function required for the asymptotic distribution for the SMM estimator (Lee and Ingram 1991). Finally, we use simulated annealing to ensure a global search for $\widehat{\mathbf{c}}$.

3.2.3 Results of SMM Estimation and Tests

Table 3 shows the SMM estimation and tests. Panel A shows that costly reversibility is highly significant. The downward adjustment cost parameter, θ^{-}, is estimated to be 508.18 ($t = 13.39$). In contrast, the upward adjustment cost parameter, θ^{+}, is small by comparison, 0.63 ($t = 4.6$). Operating leverage is also significant, with the fixed cost of production, f, estimated to be 0.0637 ($t = 4.24$). Finally, the conditional volatility of firm-specific productivity is 0.158 ($t = 8.07$).

The standard investment model does a good job in matching the moments. For the overidentification test, the p-value of 0.59 indicates that the model cannot be rejected with the seven moments in question (Panel B). For the individual moments, the model errors are all economically small and mostly insignificant (Panel C). For investment rate moments, the cross-sectional volatility is 61.99% per annum in the model, relative to 58.48% in the data. The fraction of negative investment rates is 5.78% in the model, which is close to 5.79% in the data. The model also does well in matching the cross-sectional skewness (3.345 versus 3.439) and first-order autocorrelation (26.5% versus 25.5%).

For the return moments, the value premium is on average 0.427% per month in the model, which is close to 0.429% in the data. The cross-sectional volatility is 56.41% per annum in the model, relative to 54.26% in the data. Another interesting moment is the cross-sectional skewness of individual stock excess returns, 1.384 in the data. The model moment comes close at 1.358.

In sum, the standard investment model succeeds in explaining the average value premium, while simultaneously matching the cross-sectional volatility of investment rates. Costly reversibility and operating leverage are both highly significant in formal econometric tests.

3.2.4 Additional Quantitative Results

Table 4 reports more model moments, including those not targeted in the SMM estimation. The average investment rate is 30.4% per annum in the model, which is lower than 38.4% in the data. The investment rates in the standard model contain only organic growth, whereas the investment rates in the data also account for M&As. Removing large M&As, in which the target's assets are at least 15% of the acquirer's, reduces the average investment rate in the data to 34.8% in the data (Table A1).

In addition, as noted, the depreciation rate in the model is constant, whereas the depreciation rate distribution is right skewed and leptokurtic in the data (Panel B of Figure 3). Incorporating a right skewed depreciation rate distribution is likely to further increase the average investment rate in the model. The excess kurtosis of investment rates is 12.8 in the model, which is lower than 15.6 in the data. Modeling stochastic depreciation rates is also likely to improve the model's fit of kurtosis.

More important, the fraction of inactive investment rates is 49.13% in the model, which is substantially higher than 1.46% in the data. A similar result is also present in the plant-level estimation of Cooper and Haltiwanger (2006), who attribute it to capital heterogeneity. Capital is homogeneous in the model but heterogeneous in the data. Firms most likely face different adjustment costs when, for instance, constructing a new building versus buying new laptops. Smoothing over heterogeneous capital goods likely yields a lower fraction of inactive investment rates in the data, but this smoothing effect is entirely absent in the model. For this reason, Cooper and Haltiwanger do not target the fraction of inactive investment rates in their estimation. We follow the same practice.

The model implies an average value premium of 0.42% per month, with a t-value of 1.97 (Panel B of Table 4).[9] Although the t-value is not targeted in the SMM, it is not far from 2.28 in the data.

Panel C reports the other return moments in the model. As direct targets of SMM, the cross-sectional volatility of annual returns is 55.6%, which is close to 54.3% in the data, and the cross-sectional skewness is 1.36, which is also close to 1.38 in the data. For monthly returns, the comparison in volatility is between 13.55% and 13.33%, and that in skewness is between 1.04 and 0.66. For 5-year returns, the comparison in volatility is between 193.4% and 188.8%, and skewness between 2.16 and 2.32. Although not a direct target of SMM, the model also reproduces a leptokurtic stock return distribution. The excess kurtosis coefficients are 4.01, 2.83, and 5.76 for the monthly, annual, and 5-year returns in the model, relative to 2.23, 3.56, and 7.03 in the data, respectively.

3.2.5 Comparative Statics

To gain intuition of the model's performance, we conduct an extensive set of comparative statics: (i) A low downward adjustment cost parameter, $\theta^- = 10$; (ii) a low upward adjustment cost parameter, $\theta^+ = 0.3$; (iii) a low fixed cost of production, $f = 0.03$; and (iv) a low conditional volatility of firm-specific productivity, $\sigma_z = 0.145$. These four experiments correspond to the four parameters in the SMM. We also vary two predetermined parameters that are not pinned down tightly via prior estimates (Section 3.2.1): (v) A low persistence of firm-specific productivity, $\rho_z = 0.96$; and (vi) a low long-term mean of aggregate productivity, $\overline{x} = -3.25$. In each experiment, we only change the parameter in question, while keeping all the other parameters fixed at the benchmark values.

Downward Adjustment Costs, θ^- Table 5 shows the results from the comparative statics. In the first experiment, reducing the downward adjustment cost parameter, θ^-, from 508.2 to 10 has a dramatic impact on the average value premium and the investment rate moments. The immediate impact is on the fraction of negative investment rates, rising drastically from 5.75% to 47.77%.

[9] The seven targeted moments in the model in Table 4 differ slightly from those in Table 3. The reason is that Table 4 is generated outside the SMM estimation and is based on a different set of random shocks.

Intuitively, because disinvesting is less costly, the investment rates become more frequently negative. As a coronary, the investment rates also become substantially more volatile, with the cross-sectional volatility spiking up from 61.9% to 105.5% per annum. As the adjustment costs are less asymmetric, the firm-level investment rate distribution also becomes less asymmetric and less leptokurtic, with skewness falling from 3.34 to 2.91 and excess kurtosis 12.79 to 9.93. All these changes strongly indicate the importance of costly reversibility in driving the key properties of firm-level investment rates. However, the persistence of investment rates barely changes as a result of the fall in θ^-.

A fall in the downward adjustment cost parameter, θ^-, also affects the return moments. Most important, the average value premium falls from 0.42% per month ($t = 1.97$) in the benchmark model with $\theta^- = 508.2$ to only 0.14% ($t = -0.3$) with $\theta^- = 10$. The t-value is weakly negative, despite a weakly positive value premium, because we report the cross-simulation averages across 500 simulations. This result confirms the asymmetry mechanism for the value premium. A related mechanism goes through operating leverage. The average capital in simulations increases from 12.6 to 14.9. Because the fixed cost of production, f, remains unchanged, the operating leverage becomes weaker, reinforcing the weaker asymmetry mechanism to yield a weaker value premium.

Finally, relative to the cross-sectional investment rate moments (volatility, skewness, and kurtosis), the quantitative impact of θ^- on the cross-sectional return moments is small.

Upward Adjustment Costs, θ^+ In the second experiment, we reduce the upward adjustment cost parameter, θ^+, from 0.63 to 0.3. The most visible impact of this change is the lower persistence of investment rates, 21.5%, relative to 26.5% in the benchmark model. Intuitively, because the investment rates are mostly positive, the persistence of investment rates is largely controlled by θ^+. By comparison, the other parameters have mostly small impact on the persistence. In addition, as positive investments become less costly, the investment rate distribution becomes more volatile, asymmetric, and leptokurtic. However, the fraction of negative investment rates rises only slightly. Finally, the average value premium falls to 0.26% per month ($t = 1.04$). Intuitively, the average capital increases somewhat to 13.25, which weakens the operating leverage mechanism.

Fixed Cost of Production, f The third experiment, in which we lower f from 0.0637 to 0.03, shows the big impact of operating leverage in the model, lending support to Carlson, Fisher, and Giammarino 2004). The average value premium becomes significantly negative, -0.31% per month ($t = -2.32$). A weaker operating leverage also reduces the cross-sectional volatility of stock returns from 55.6% to 30.9% per annum, the skewness from 1.36 to 1.16, and excess kurtosis from 2.83 to 1.73. The cross-sectional volatility, skewness, and kurtosis of investment rates also drop. Finally, as firms are more profitable, the fraction of negative investment rates falls to 4.27%.

Conditional Volatility of Firm-specific Productivity, σ_z Reducing σ_z from 0.158 to 0.145 raises the average value premium to 0.81% per month ($t = 2.82$). Intuitively, as the cross-sectional productivity dispersion becomes smaller, the average capital in the economy is also smaller, 9.86, falling from 12.63 from the benchmark model. Intuitively, because of costly reversibility, a fall in the magnitude of exogenous firm-specific shocks impacts on positive investment rates more than negative investment rates. Accordingly, a second-moment fall in σ_z gives rise to a first-moment drop in the average capital. The drop in the average capital raises the operating leverage, which in turn increases the average value premium. The higher operating leverage also increases all the cross-sectional return moments. However, the investment rate moments are largely unaffected.

Persistence of Firm-specific Productivity, ρ_z Reducing ρ_z works similarly as lowering σ_z. Varying ρ_z from 0.97 to 0.96 raises the average value premium to 0.99% per month ($t = 3.23$). As the unconditional productivity dispersion becomes smaller, the average capital in simulations falls to 7.61, giving rise to a higher operating leverage. The cross-sectional volatility, skewness, and kurtosis of individual stock returns all rise greatly. These moments of investment rates also rise, but the impact is small. Finally, as the firm-specific productivity becomes less persistent, the investment rates are also less persistent, with the autocorrelation falling from 26.5% to 22.2%.

Long-term Average Aggregate Productivity, $\overline{x}$ Reducing $\overline{x}$ from -3.18 to -3.25 lowers the size of the economy, with the average capital falling to 9.41. As a result of a higher operating leverage, the average value premium rises to 0.85% per month ($t = 3.02$). The cross-sectional volatility, skewness, and kurtosis of individual returns all rise greatly. These moments of investment rates also increase, and the changes are larger than those from reducing ρ_z. The crux is that x_t appears not only in firms' production function but also in the pricing kernel given by equation (7). As such, the aggregate productivity has a larger impact on firms' decisions than the firm-specific productivity.

4 Conclusion

This paper revisits the role of costly reversibility in the cross section of expected returns. In the 1962–2018 sample, which ontains 175,025 firm-year observations in Compustat, the firm-level investment rate distribution is highly skewed to the right, with a small fraction of negative investment rates (below -1%), 5.79%, a tiny fraction of inactive investment rates (between -1% and 1%), 1.46%, and a large fraction of positive investment rates (above 1%), 92.75%. Surprisingly, the firm-level evidence is even stronger than the plant-level evidence in Cooper and Haltiwanger (2006).

Quantitatively, SMM estimation and tests show that the standard investment model explains the average value premium, while simultaneously matching the cross-sectional volatility and skewness of firm-level investment rates as well as the fraction of negative investment rates. The combination of costly reversibility and operating leverage plays a prominent role in the model's performance.

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Table 1 : Time Series Averages of Cross-sectional Moments of Annual Gross Investment Rates, 1962–2018, 175,025 Firm-year Observations

We exclude financials, firms with negative book equity, and firm-year observations with nonpositive total assets, net property, plant, and equipment, or sales. Capital, K_{it}, is net property, plant, and equipment (Compustat annual item PPENT). The depreciation rate, δ_{it}, is depreciation and amortization (item DP) minus the amortization of intangibles (item AM, zero if missing), scaled by PPENT. In Panel A, the gross investment rate, I_{it}/K_{it}, is the net investment rate, $(K_{it+1}-K_{it})/K_{it}$, plus the depreciation rate, δ_{it}. Panel B uses an alternative investment rate, capital expenditure (item CAPX) minus sales of PPE (item SPPE, zero if missing), scaled by PPENT. Each year we winsorize the gross investment rates at the 1%–99% level for the pooled firm-year observations of the fiscal years ending in the calendar year. We show time series averages (as well as time series standard errors adjusted for heteroscedasticity and autocorrelations, denoted Ste) of cross-sectional mean (Mean), standard deviation (Std), skewness (Skew), excess kurtosis (Kurt, relative to the kurtosis of three for the normal distribution), percentiles (5th, 25th, 50th, 75th, and 95th), the first-order autocorrelation via cross-sectional regressions (ρ_1), the fraction of observations with gross investment rates less than -1% (negative, $\%_I^-$) and between -1% and 1% (inactive, $\%_I^0$). The moments except for skewness and kurtosis are in percent.

Panel A: Gross investment rates (net growth rates of PPENT plus depreciation rates)												
	Mean	Std	Skew	Kurt	5th	25th	50th	75th	95th	ρ_1	$\%_I^-$	$\%_I^0$
Estimate	38.41	58.48	3.44	15.58	-3.65	11.00	22.43	43.71	132.93	25.52	5.79	1.46
Ste	2.01	4.58	0.12	0.96	0.82	0.34	0.76	2.04	8.60	0.78	0.35	0.08
Panel B: (CAPX − SPPE)/PPENT												
	Mean	Std	Skew	Kurt	5th	25th	50th	75th	95th	ρ_1	$\%_I^-$	$\%_I^0$
Estimate	31.48	37.51	3.05	12.17	2.65	11.55	20.57	36.82	97.90	39.02	2.03	1.30
Ste	1.10	2.41	0.10	0.75	0.33	0.33	0.49	1.14	4.82	1.10	0.24	0.11

Table 2 : Cross-sectional Moments of Excess Stock Returns in the Data, January 1962–December 2018

We exclude financials, firms with negative book equity, and firm-year observations with nonpositive total assets, net property, plant, and equipment, or sales. Excess returns are in excess of one-month Treasury bill rates. Panel A shows the average excess returns, $\overline{R}$, and their t-values, $t_{\overline{R}}$, for the book-to-market deciles. At the end of June of each year t, we split stocks into deciles based on the NYSE breakpoints of book-to-market equity (Bm), which is the book equity for the fiscal year ending in calendar year $t-1$ divided by the market equity (from CRSP) at the end of December of $t-1$. For firms with more than one share class, we merge the market equity for all share classes before computing Bm. Book equity is stockholders' book equity, plus balance sheet deferred taxes and investment tax credit (Compustat annual item TXDITC) if available, minus the book value of preferred stock. Stockholders' equity is the value reported by Compustat (item SEQ), if it is available. If not, we measure stockholders' equity as the book value of common equity (item CEQ) plus the par value of preferred stock (item PSTK), or the book value of assets (item AT) minus total liabilities (item LT). Depending on availability, we use redemption (item PSTKRV), liquidating (item PSTKL), or par value (item PSTK) for the book value of preferred stock. Monthly decile returns are from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$. In Panel B, annual returns are nonoverlapping annual observations from compounding 12 monthly returns within a given year, and 5-year returns are nonoverlapping 5-year observations from compounding 60 monthly returns within a given 5-year interval. We report time series averages (as well as time series standard errors adjusted for heteroscedasticity and autocorrelations, denoted Ste) of cross-sectional mean (Mean), standard deviation (Std), skewness (Skew), excess kurtosis relative to three for the normal distribution (Kurt), percentiles (5th, 25th, 50th, 75th, and 95th). We winsorize excess returns at the 1%–99% level for each month. Returns are in percent.

Panel A: Average excess returns of the book-to-market deciles

	Low	2	3	4	5	6	7	8	9	High	H−L
$\overline{R}$	0.42	0.53	0.58	0.48	0.53	0.59	0.65	0.68	0.72	0.85	0.43
$t_{\overline{R}}$	2.01	2.83	3.21	2.56	3.14	3.42	3.75	3.84	3.92	3.85	2.28

Panel B: Time series averages of cross-sectional moments of individual excess returns

	#Stocks	Mean	Std	Skew	Kurt	5th	25th	50th	75th	95th
Monthly	3,632	0.53	13.33	0.66	2.23	−19.59	−6.86	−0.36	6.62	23.76
Ste		0.26	0.29	0.03	0.07	0.51	0.28	0.21	0.27	0.68
Annual	3,278	9.78	54.26	1.38	3.56	−57.94	−23.84	1.00	30.28	110.36
Ste		3.40	3.22	0.10	0.39	3.16	2.97	2.80	3.46	8.74
5-year	2,283	80.94	188.77	2.32	7.03	−90.32	−34.97	28.96	125.82	455.96
Ste		27.86	25.83	0.16	0.88	9.88	14.63	19.94	30.79	81.97

Table 3 : SMM Estimation and Tests, 1962–2018

This table reports the results for our SMM estimation and tests. We estimate four parameters, including the upward (θ^+) and downward (θ^-) adjustment cost parameters, the fixed cost of production (f), and the conditional volatility of firm-specific productivity shocks (σ_z) to match seven data moments. The moments include four moments of annual gross investment rates (the time series averages of cross-sectional standard deviation, Std; skewness, Skew; first-order autocorrelation, ρ_1; and the fraction of negative investment rates, $\%_I^-$) and three moments of excess stock returns (the time series averages of cross-sectional standard deviation, Std; skewness, Skew; and the value premium, $\overline{R}_{\mathrm{H-L}}$). The average value premium is in monthly percent. Panel A reports the parameter estimates and their t-values. Panel B shows the test of overidentification, including the test statistic, χ^2; the degree of freedom, d.f.; and the p-value of the χ^2 statistic. Finally, Panel C shows the data and model moments as well as the t-values of the individual errors.

	Panel A: Parameter estimates				Panel B: The χ^2 test		
	θ^+	θ^-	f	σ_z	χ^2	d.f.	p-value
Estimate	0.6312	508.1751	0.0637	0.1580	1.9306	3	0.5869
t-value	4.5978	13.3923	4.2412	8.0705			

	Panel C: Individual moments and the significance of their model errors						
	Gross investment rates				Returns		
	Std	Skew	ρ_1	$\%_I^-$	Std	Skew	$\overline{R}_{\mathrm{H-L}}$
Data	0.5848	3.4385	0.2546	0.0579	0.5426	1.3836	0.4289
Model	0.6199	3.3448	0.2653	0.0578	0.5641	1.3581	0.4269
t(Diff)	−1.39	0.94	−1.37	4.50	−1.01	0.42	0.74

Table 4 : Model Moments with the Predetermined and Estimated Parameters

Results are based on 500 artificial panels from monthly simulations of the benchmark model. From arbitrary initial conditions, we use 300 months as the burn-in period to reach the ergodic distribution. We then draw 500 artificial panels, each with 5,000 firms and 684 months (57 years). In Panel A, we time-aggregate monthly to annual investments by summing up the 12 monthly observations within a given year. Annual gross investment rate is annual investment over the beginning-of-year capital. On each artificial panel, we winsorize the gross investment rates at the 1%–99% level for each year. We calculate time series averages of cross-sectional mean, standard deviation (Std), skewness (Skew), excess kurtosis (Kurt, relative to the kurtosis of three for the normal distribution), percentiles (5th, 25th, 50th, 75th, and 95th), the first-order autocorrelation via cross-sectional regressions (ρ_1), the fraction of observations with gross investment rates less than -1% (negative, $\%_I^-$) and between -1% and 1% (inactive, $\%_I^0$). The investment rate moments except for skewness and kurtosis are in percent. In Panel B, at the end of June of each year t, we sort stocks into deciles on book-to-market, which is capital, K_{it}, divided by the ex dividend firm value, $V_{it} - D_{it}$, in the model. Monthly decile returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$. In Panel C, annual returns are nonoverlapping annual observations from compounding 12 monthly returns within a given year, and 5-year returns are nonoverlapping 5-year observations from compounding 60 monthly returns within a given 5-year interval. On each panel, we winsorize monthly excess returns at the 1%–99% level for each month. We calculate time series averages of cross-sectional mean (Mean), volatility (Std), skewness (Skew), excess kurtosis (Kurt, relative to three for the normal distribution), percentiles (5th, 25th, 50th, 75th, and 95th). Returns are in percent. For all the moments, the table reports cross-simulation averages and standard deviations (CS-std) across the 500 artificial panels.

Panel A: Gross investment rates

	Mean	Std	Skew	Kurt	5th	25th	50th	75th	95th	ρ_1	$\%_I^-$	$\%_I^0$
Estimate	30.42	61.88	3.34	12.79	−0.78	−0.41	3.21	31.38	156.32	26.53	5.75	49.12
CS-std	1.78	3.26	0.15	1.32	0.07	0.15	1.12	2.10	7.35	0.62	3.01	1.48

Panel B: Average excess returns of the book-to-market deciles

	Low	2	3	4	5	6	7	8	9	High	H−L
$\overline{R}$	0.68	0.66	0.65	0.66	0.70	0.72	0.73	0.77	0.88	1.10	0.42
CS-std	0.13	0.14	0.14	0.15	0.16	0.18	0.18	0.21	0.27	0.37	0.29
$t_{\overline{R}}$	2.74	2.77	2.77	2.78	2.79	2.80	2.82	2.82	2.81	2.81	1.97
CS-std	0.65	0.65	0.64	0.64	0.63	0.64	0.63	0.62	0.60	0.55	0.65

Panel C: Time series averages of cross-sectional return moments

	Mean	Std	Skew	Kurt	5th	25th	50th	75th	95th
Monthly	1.02	13.55	1.04	4.01	−20.66	−1.95	0.17	2.17	30.31
CS-std	0.33	2.26	0.09	0.50	2.23	0.63	0.19	0.63	4.07
Annual	12.01	55.60	1.36	2.83	−53.73	−23.42	0.80	33.43	117.64
CS-std	4.27	12.30	0.08	0.44	7.32	4.42	2.59	5.54	25.02
5-year	57.53	193.36	2.16	5.76	−102.87	−60.04	−2.97	99.95	433.68
CS-std	66.41	212.77	0.16	0.97	28.19	29.31	24.44	48.04	352.07

Table 5 : Comparative Statics

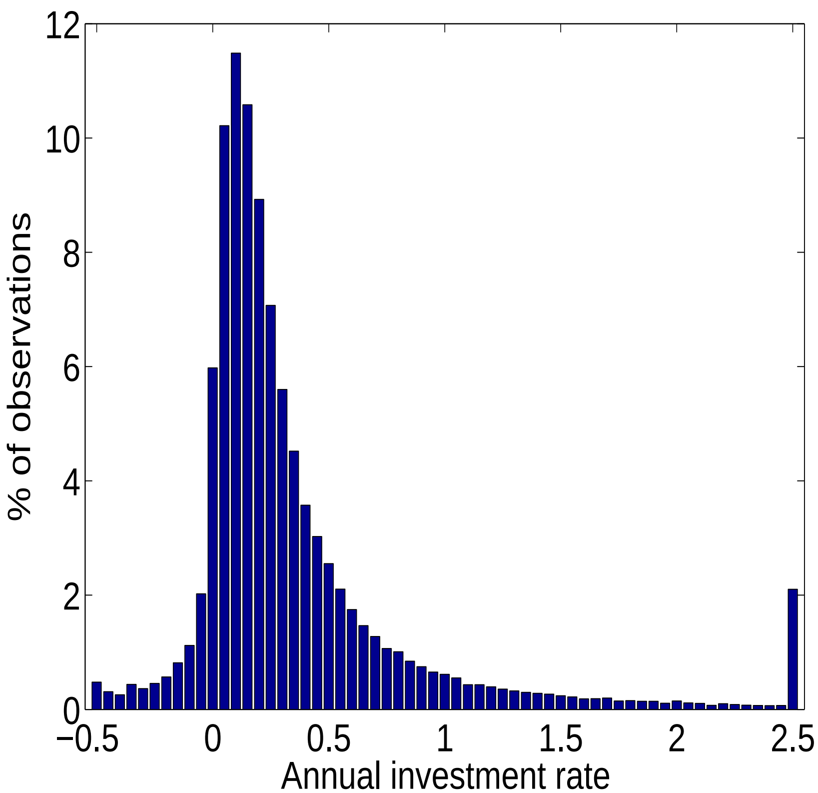
Results are from 500 artificial panels from monthly simulations of the model with the benchmark calibration as well as six comparative statics: (i) a low downward parameter in quadratic adjustment costs, $\theta^- = 10$; (ii) a low upward parameter in quadratic adjustment costs, $\theta^+ = 0.3$; (iii) a low fixed cost of production, $f = 0.03$; (iv) a low conditional volatility of firm-specific productivity, $\sigma_z = 0.145$; (v) a low persistence of firm-specific productivity, $\rho_z = 0.96$; and (vi) a low long-term average log aggregate productivity, $\overline{x} = -3.25$. In each experiment, we only change the parameter in question, while keeping all the other parameters at the same values as in the benchmark model. For each experiment, from arbitrary initial conditions, we use 300 months as the burn-in period to reach the ergodic distribution. We draw 500 artificial panels, each with 5,000 firms and 684 months. We time-aggregate monthly to annual investments by summing up the 12 monthly observations within a given year. Annual gross investment rate is annual investment over the beginning-of-year capital. On each panel, we winsorize the gross investment rates at the 1%–99% level for each year. We calculate time series averages of cross-sectional mean (Mean), standard deviation (Std), skewness (Skew), excess kurtosis (Kurt), the first-order autocorrelation via cross-sectional regressions (ρ_1), and the fraction of observations with gross investment rates less than -1% ($\%_I^-$). $\overline{R}_{\mathrm{H-L}}$ is the average return of the high-minus-low book-to-market decile (the value premium), and $t_{\overline{R}}$ its t-value. For annual individual excess returns, the columns denoted "Std," "Skew," and "Kurt" are the time series averages of the cross-sectional standard deviation, skewness, and excess kurtosis of stock excess returns. Annual returns are nonoverlapping annual observations from compounding 12 monthly returns within a given year. K_{ss} is the average capital in simulations. The moments except for $t_{\overline{R}}$, skewness, kurtosis, and K_{ss} are in percent

			Gross investment rates						Annual returns			
	$\overline{R}_{\mathrm{H-L}}$	$t_{\overline{R}}$	Mean	Std	Skew	Kurt	ρ_1	$\%_I^-$	Std	Skew	Kurt	K_{ss}
Benchmark	0.42	1.97	30.42	61.88	3.34	12.79	26.53	5.75	55.60	1.36	2.83	12.63
θ^-, 10	0.14	−0.30	48.39	105.52	2.91	9.93	27.46	47.77	54.84	1.36	2.77	14.92
θ^+, 0.3	0.26	1.04	32.59	72.24	3.61	14.79	21.46	6.24	53.01	1.33	2.66	13.25
f, 0.03	−0.31	−2.32	29.42	57.01	3.20	11.76	27.48	4.27	30.87	1.16	1.73	12.64
σ_z, 0.145	0.81	2.82	30.49	61.17	3.34	12.82	25.97	6.21	67.06	1.46	3.80	9.86
ρ_z, 0.96	0.99	3.23	31.94	64.86	3.40	13.46	22.17	6.35	74.90	1.62	4.83	7.61
$\overline{x}$, −3.25	0.85	3.02	31.99	69.13	3.53	14.15	24.57	7.84	76.60	1.67	4.61	9.41

Figure 1 : The Cross-sectional Distribution of Gross Annual Investment Rates

Panel A shows the firm-level gross investment rate distribution in Compustat from 1962 to 2018 (57 years), with 175,025 firm-year observations. We exclude financials, firms with negative book equity, and firm-year observations with nonpositive total assets, net property, plant, and equipment, or sales. Capital, K_{it}, is net property, plant, and equipment (Compustat annual item PPENT). The depreciation rate, δ_{it}, is the amount of depreciation and amortization (item DP) minus the amortization of intangibles (item AM, zero if missing), scaled by item PPENT. The gross investment rate, I_{it}/K_{it}, is the net investment rate, $(K_{it+1} - K_{it})/K_{it}$, plus the depreciation rate, δ_{it}. Each year we winsorize the gross investment rates in the full sample at the 1%–99% level for the pooled firm-year observations of the fiscal years ending in a given calendar year. Panel B, which is borrowed from Cooper and Haltiwanger's (2006) Figure 1, shows the plant-level gross annual investment rate distribution based on a balanced panel with about 7,000 large, manufacturing plants in continuous operating between 1972 and 1988 from the U.S. Census Bureau Longitudinal Research Database.

Panel A: Compustat, 1962–2018, 175,025 firm-year observations



Panel B: Cooper and Haltiwanger (2006), 1972–1988, 119,000 plant-year observations, Longitudinal Research Database

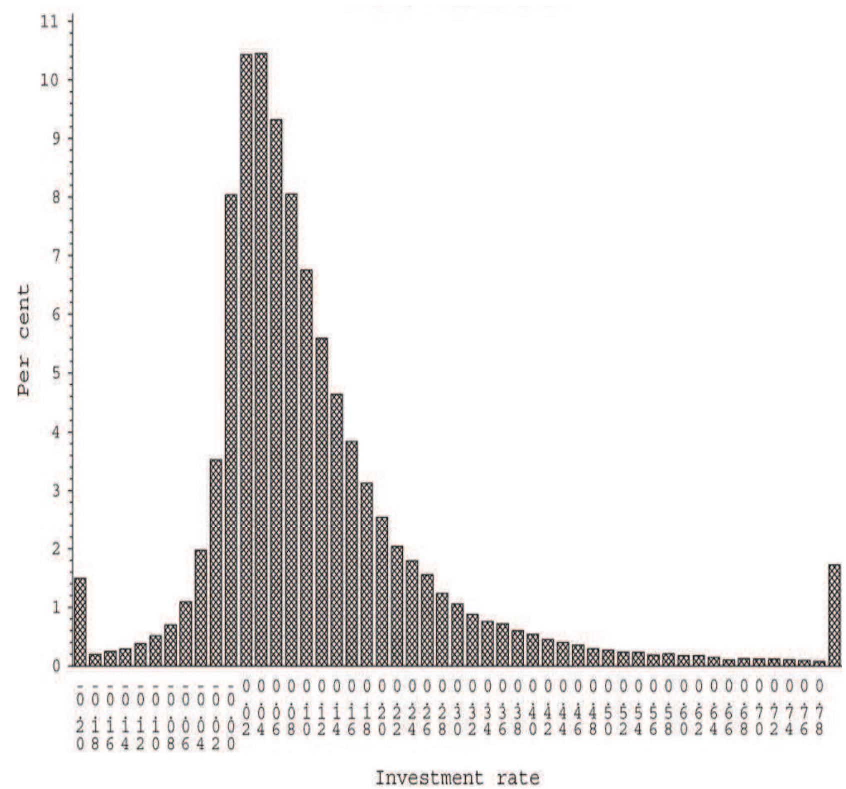


Figure 2 : The Cross-sectional Distribution of Gross Quarterly Investment Rates, 1978:Q1–2016:Q4

Panel A is Clementi and Palazzo's (2019) Figure 1 for the quarterly sample from 1978 to 2016. Panel B is our replication. We exclude financials, firms with negative book equity, and firm-quarter observations with nonpositive total assets, net property, plant, and equipment, or sales. Capital, K_{it}, is net property, plant, and equipment (Compustat quarterly item PPENTQ). The depreciation rate, δ_{it}, is the amount of depreciation and amortization (item DPQ) minus the amortization of intangibles (annual item AM divided by four, zero if missing), scaled by item PPENTQ. The gross investment rate, I_{it}/K_{it}, is the net investment rate, $(K_{it+1} - K_{it})/K_{it}$, plus the depreciation rate, δ_{it}. For the pooled firm-quarter observations of the fiscal quarters ending in a given calendar quarter, we winsorize gross investment rates at the 1%–99% level. Our replication sample contains in total 463,426 firm-quarter observations.

Panel A: Clementi and Palazzo (2019) | Panel B: Our replication

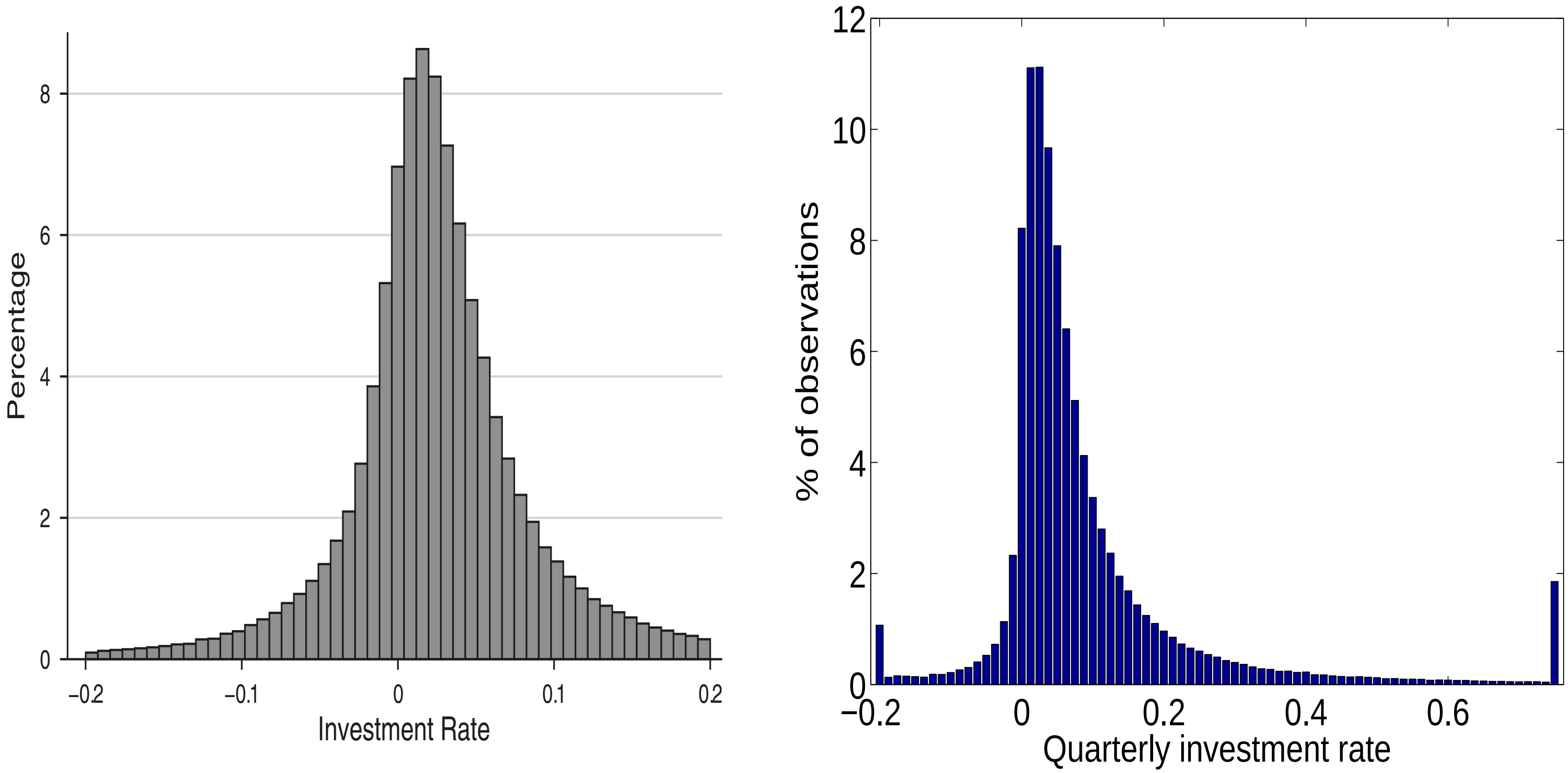


Figure 3 : The Cross-sectional Distributions of Quarterly BEA Industry-level and Compustat Firm-level Depreciation Rates, 1978:Q1–2016:Q4

We exclude financials, firms with negative book equity, and firm-quarter observations with nonpositive total assets, net property, plant, and equipment, or sales. The sample contains in total 463,426 firm-quarter observations. Panel A reports the firm-level distribution of the quarterly BEA average industry-level depreciation rates assigned to the firm level based on the SIC or NAICS codes. The BEA depreciation rates are computed across the 2- or 3-digit NAICS industries. Prior to June 1985, when NAICS codes become available, we use SIC codes and convert them into NAICS codes using the mapping tables from the Census Bureau. The Compustat firm-level depreciation rate, δ_{it}, is the amount of depreciation and amortization (item DPQ) minus the amortization of intangibles (annual item AM divided by four, zero if missing), scaled by item PPENTQ. For the pooled firm-quarter observations of the fiscal quarters ending in a given calendar quarter, we winsorize the depreciation rates at the 1%–99% level.

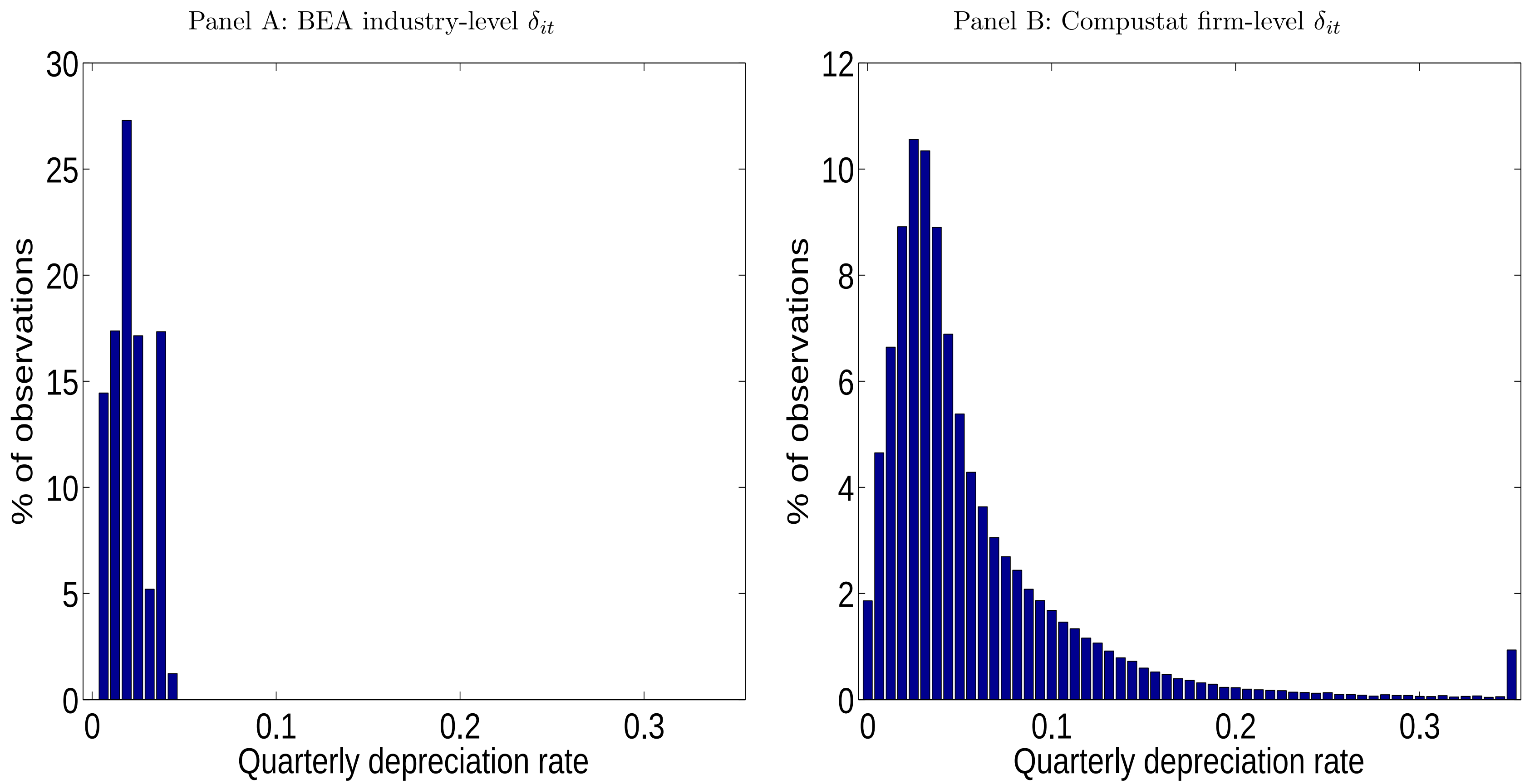
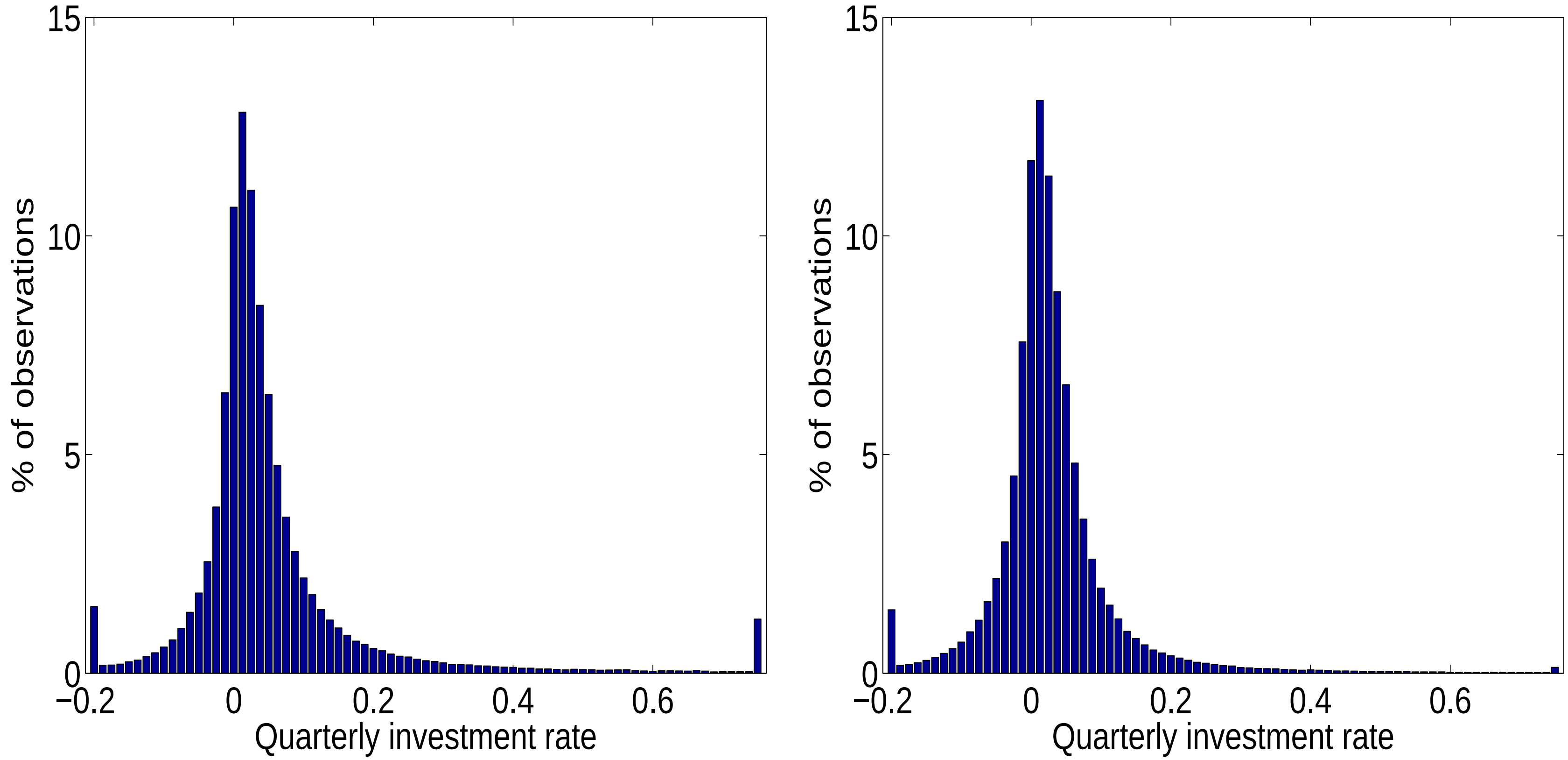


Figure 4 : The Cross-sectional Distribution of Gross Quarterly Investment Rates Measured with BEA Industry-level Depreciation Rates, 1978:Q1–2016:Q4

Gross quarterly investment rates are computed as the sum of quarterly net growth rates of net PPE and BEA's average industry-level depreciation rates assigned to the firm level based on the SIC or NAICS codes. BEA's depreciation rates are across the 2- or 3-digit NAICS industries. Prior to June 1985, when NAICS codes become available, we use SIC codes and convert them into NAICS codes using the mapping tables from the Census Bureau. Our replication sample (463,426 firm-quarter observations) in Panel A excludes financials, firms with negative book equity, and firm-quarter observations with nonpositive total assets, net property, plant, and equipment, or sales. For the pooled firm-quarter observations of the fiscal quarters ending in a given calendar quarter, we winsorize the gross investment rates at the 1%–99% level. The reproduction sample (295,155 firm-quarter observations) in Panel B imposes Clementi and Palazzo's (2019) more stringent sample criteria: (i) Excluding financial firms, utilities, and unclassified firms (SIC $\geq$ 9000); (ii) dropping firms with fewer than 12 past quarterly investment rates (i.e., dropping the first 12 quarterly investment rate observations); (iii) dropping firm-quarter observations associated with acquisitions larger than 5% of total assets; (iv) discarding firm-quarter observations in the top and bottom 0.5% of the pooled distribution of quarterly investment rates; and (v) dropping firm-quarter observations with missing values of investment rates or book-to-market.

Panel A: Our replication sample

Panel B: Our reproduction sample



A Industries

We classify firms into ten industries based on their SIC codes at each fiscal year end (Compustat item SICH or CRSP item SICCD):

1. NoDur (consumer nondurables, including food, tobacco, textiles, apparel, leather, toys): 0100–0999, 2000–2399, 2700–2749, 2770–2799, 3100–3199, 3940–3989.
2. Durbl (consumer durables, including cars, TV's, furniture, household appliances): 2500–2519, 2590–2599, 3630–3659, 3710–3711, 3714–3714, 3716–3716, 3750–3751, 3792–3792, 3900–3939, 3990–3999.
3. Manuf (manufacturing, including machinery, trucks, planes, chemicals, office furniture, paper, printing): 2520–2589, 2600–2699, 2750–2769, 2800–2829, 2840–2899, 3000–3099, 3200–3569, 3580–3621, 3623–3629, 3700–3709, 3712–3713, 3715–3715, 3717–3749, 3752–3791, 3793–3799, 3860–3899.
4. Enrgy (oil, gas, and coal extraction and products): 1200–1399, 2900–2999.
5. HiTec (business equipment, including computers, software, and electronic equipment): 3570–3579, 3622–3622, 3660–3692, 3694–3699, 3810–3839, 7370–7379, 7391–7391, 8730–8734.
6. Telcm (telephone and television transmission): 4800-4899
7. Shops (wholesale, retail, and some services such as laundries and repair shops): 5000–5999, 7200–7299, 7600–7699.
8. Hlth (healthcare, medical equipment, and drugs): 2830–2839, 3693–3693, 3840–3859, 8000–8099.
9. Utils (utilities): 4900–4949.
10. Other (others, including mines, construction, transportation, hotels, business Service, and entertainment).

Note that Fama and French (1997) include firms in the financial sector in "Other" but we exclude these firms. Also, due to missing SIC codes, we lose 3,814 firm-year observations.

For each fiscal year, we split the full sample in Table 1 into 10 industry-specific subsamples, based on firms' SIC codes (Compustat item SICH or CRSP item SICCD) at the fiscal year end. The industries include consumer nondurables (NoDur), consumer durables (Durbl), manufacturing (Manuf), energy (Enrgy), high tech (HiTec), telecommunication (Telcm), shops (Shops), health care (Hlth), utilities (Utils), and others (Other).

B Computation

To solve equation (8), we adopt the value function iteration method on the discrete state space (Burnside 1999). We use a grid with 150 points for capital, $K_{it} \in (\underline{K}, \overline{K})$, in which $\underline{K} = 0.01$ and $\overline{K} = 1,000$ (the long-term average K_{it} in simulations is slightly above ten). The lower and upper bounds of capital are chosen to make the range large enough to be nonbinding in all simulations. We construct the capital grid recursively: $K_g = K_{g-1} + \phi_1 \exp(\phi_2(g-2))$, for $g = 2, 3, \ldots, 150$ is the index of grid points, and ϕ_1 and ϕ_2 are two constants that are chosen to provide the desired number of grid points and the grid's upper bound, given a predetermined lower bound of $K_1 = \underline{K} = 0.01$.

To convert the aggregate and firm-specific productivity processes, x_t and z_{it}, respectively, defined on the continuous state space to Markov chains defined on the discrete state space, we adopt the Rouwenhorst (1995) method. We use 17 grid points for both x_t and z_{it}. The grids are large enough to cover four unconditional standard deviations above and below their respective unconditional mean. We also simulate directly from the discrete state spaces of x_t and z_{it}. For the continuous state space of K_{it}, we use the piecewise linear interpolation extensively to obtain the optimal decisions of firms with capital stocks that are not directly on the K_{it} grid.

To compute the optimization on the right-hand side of equation (8), we use a straightforward but highly reliable global search algorithm. We construct a dense grid for the next period's capital, K_{it+1}, by placing 100 even-spaced points between any two adjacent points on the grid of current capital, K_{it}. We calculate the objective function on each point on the K_{it+1} grid and take the maximum.

Table A1 : Time Series Averages of Cross-sectional Moments of Annual Gross Investment Rates in the No-large-M&A Sample, 1962–2018, 164,723 Firm-year Observations

We exclude financials, firms with negative book equity, and firm-year observations with nonpositive total assets, net property, plant, and equipment, or sales. Capital, K_{it}, is net property, plant, and equipment (Compustat annual item PPENT). The depreciation rate, δ_{it}, is the amount of depreciation and amortization (item DP) minus the amortization of intangibles (item AM, zero if missing), scaled by PPENT. In Panel A, the gross investment rate, I_{it}/K_{it}, is the net investment rate, $(K_{it+1} - K_{it})/K_{it}$, plus the depreciation rate, δ_{it}. In Panel B, we use an alternative investment rate defined as capital expenditure (item CAPX) minus sales of PPE (item SPPE, zero if missing), scaled by PPENT. Each year we winsorize the gross investment rates in the full sample at the 1%–99% level for the pooled firm-year observations of the fiscal years ending in a given calendar year. We further impose the no-large-M&A screen by excluding firms with sizeable M&As with the target assets at least 15% of the acquirer assets. We measure M&As as the maximum of reported acquisitions from Compustat annual item AQC and the total value of all acquisitions in a given fiscal year from the Securities Data Company (SDC) dataset. When no M&A activities are reported in either database, we set the amount of M&As to zero. We report time series averages (as well as time series standard errors adjusted for heteroscedasticity and autocorrelations, denoted Ste) of cross-sectional mean (Mean), standard deviation (Std), skewness (Skew), excess kurtosis (Kurt, relative to the kurtosis of three for the normal distribution), percentiles (5th, 25th, 50th, 75th, and 95th), the first-order autocorrelation via cross-sectional regressions (ρ_1), as well as the fractions of negative investment rates (less than -1%, $\%_I^-$) and inactive investment rates (between -1% and 1%, $\%_I^0$). All the moments except for skewness and kurtosis are in percent.

	Panel A: Gross investment rates (net growth rates of net PPE plus depreciation rates)											
	Mean	Std	Skew	Kurt	5th	25th	50th	75th	95th	ρ_1	$\%_I^-$	$\%_I^0$
Estimate	34.75	52.66	3.68	18.88	−4.27	10.52	21.23	40.24	115.58	26.64	6.03	1.53
Ste	1.51	3.71	0.15	1.39	0.88	0.31	0.61	1.55	6.26	0.79	0.37	0.09
	Panel B: (CAPX − SPPE)/Net PPE											
	Mean	Std	Skew	Kurt	5th	25th	50th	75th	95th	ρ_1	$\%_I^-$	$\%_I^0$
Estimate	30.80	36.65	3.10	12.69	2.55	11.35	20.21	36.09	95.43	38.92	2.04	1.35
Ste	1.01	2.26	0.11	0.81	0.33	0.33	0.47	1.05	4.49	1.14	0.24	0.11

Table A2 : Time Series Averages of Cross-sectional Moments of Annual Gross Investment Rates, Small versus Big Firms, 1962–2018

We exclude financials, firms with negative book equity, and firm-year observations with nonpositive total assets, net property, plant, and equipment, or sales. Capital, K_{it}, is net property, plant, and equipment (Compustat annual item PPENT). The depreciation rate, δ_{it}, is depreciation and amortization (item DP) minus the amortization of intangibles (item AM, zero if missing), scaled by PPENT. The gross investment rate, I_{it}/K_{it}, is the net investment rate, $(K_{it+1} - K_{it})/K_{it}$, plus the depreciation rate, δ_{it}. Each year we winsorize the gross investment rates at the 1%–99% level for the pooled firm-year observations of the fiscal years ending in a given calendar year. We split the sample into two, small and big, based on the NYSE median of the beginning-of-fiscal-year market equity. On each subsample, we report time series averages (as well as time series standard errors adjusted for heteroscedasticity and autocorrelations, denoted Ste) of cross-sectional mean (Mean), standard deviation (Std), skewness (Skew), excess kurtosis (Kurt, relative to the kurtosis of three for the normal distribution), percentiles (5th, 25th, 50th, 75th, and 95th), the first-order autocorrelation via cross-sectional regressions (ρ_1), as well as the fractions of negative investment rates (below -1%, $\%_I^-$) and inactive investment rates (between -1% and 1%, $\%_I^0$). The moments except for skewness and kurtosis are in percent.

	Panel A: Small firms, 134,937 firm-year observations											
	Mean	Std	Skew	Kurt	5th	25th	50th	75th	95th	ρ_1	$\%_I^-$	$\%_I^0$
Estimate	40.32	61.61	3.21	13.45	-5.67	10.45	23.00	46.82	144.44	23.55	6.61	1.70
Ste	2.05	4.43	0.12	0.96	0.86	0.37	0.86	2.19	8.59	0.73	0.33	0.09
	Panel B: Big firms, 37,936 firm-year observations											
	Mean	Std	Skew	Kurt	5th	25th	50th	75th	95th	ρ_1	$\%_I^-$	$\%_I^0$
Estimate	30.67	39.18	4.40	32.57	2.65	12.40	21.04	34.96	89.68	37.96	2.99	0.70
Ste	2.15	4.85	0.26	4.42	0.66	0.36	0.62	1.77	10.49	1.83	0.35	0.07

Table A3 : Time Series Averages of Cross-sectional Moments of Annual Gross Investment Rates, Ten Fama-French Industries, 1962–2018

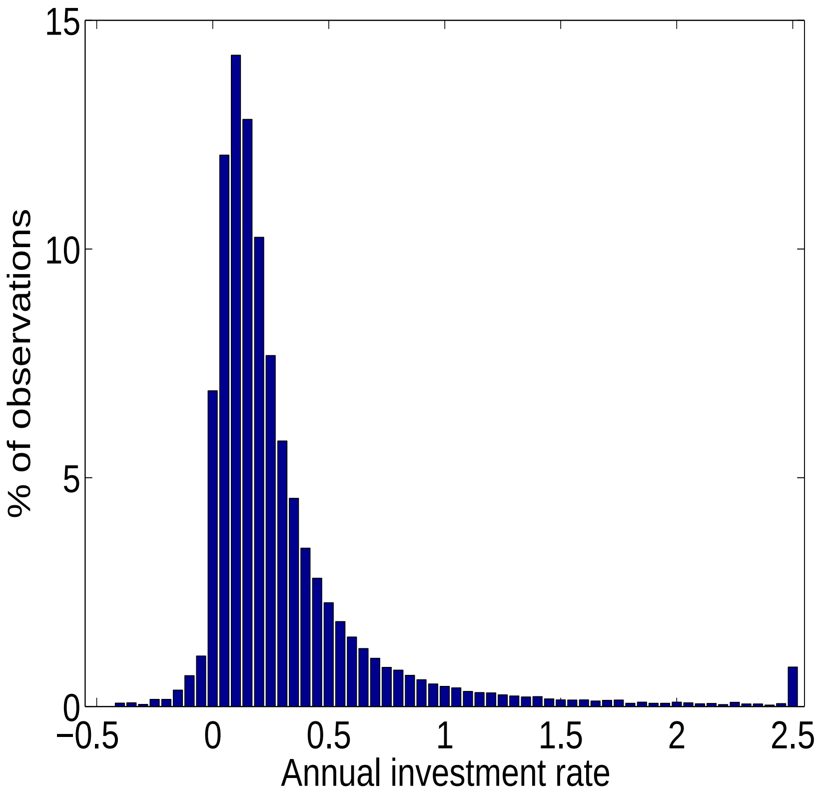
We exclude financials, firms with negative book equity, and firm-year observations with nonpositive total assets, net property, plant, and equipment, or sales. Capital, K_{it}, is net property, plant, and equipment (Compustat annual item PPENT). The depreciation rate, δ_{it}, is the amount of depreciation and amortization (item DP) minus the amortization of intangibles (item AM, zero if missing), scaled by PPENT. The gross investment rate, I_{it}/K_{it}, is the net investment rate, $(K_{it+1} - K_{it})/K_{it}$, plus the depreciation rate, δ_{it}. Each year we winsorize the gross investment rates in the full sample at the 1%–99% level for the pooled firm-year observations of the fiscal years ending in a given calendar year. We split the sample into ten industries, including consumer nondurables (NoDur), consumer durables (Durbl), manufacturing (Manuf), energy (Enrgy), high tech (HiTec), telecommunication (Telcm), shops (Shops), health care (Hlth), utilities (Utils), and others (Other). Appendix **??** classifies the industries on SIC codes. Within each industry, we report the number of firm-year observations (#obs.), time series averages (as well as time series standard errors adjusted for heteroscedasticity and autocorrelations) of cross-sectional mean (Mean), standard deviation (Std), skewness (Skew), excess kurtosis (Kurt, relative to the kurtosis of three for the normal distribution), percentiles (5th, 25th, 50th, 75th, and 95th), the first-order autocorrelation via cross-sectional regressions (ρ_1), as well as the fractions of negative investment rates (below -1%, $\%_I^-$) and inactive investment rates (between -1% and 1%, $\%_I^0$). All the moments except for skewness and kurtosis are in percent. For each industry, the first row reports the estimates, and the second row their time series standard errors adjusted for heteroscedasticity and autocorrelations.

	#obs.	Mean	Std	Skew	Kurt	5th	25th	50th	75th	95th	ρ_1	$\%_I^-$	$\%_I^0$
NoDur	15,279	30.58	46.41	3.80	22.08	−4.10	10.70	19.67	34.85	97.94	21.70	6.02	1.38
		1.25	3.73	0.20	2.22	0.82	0.29	0.41	1.07	6.05	1.73	0.34	0.11
Durbl	6,690	33.14	48.36	3.59	19.03	−4.37	12.23	21.90	36.70	104.72	20.03	5.80	1.39
		1.34	3.40	0.21	1.93	1.20	0.62	0.81	1.28	5.36	2.32	0.50	0.15
Manuf	34,298	27.91	42.79	4.39	28.74	−3.05	9.93	18.49	31.81	86.63	17.82	5.59	1.54
		1.13	2.81	0.21	2.38	0.84	0.45	0.65	1.18	4.57	1.05	0.40	0.13
Enrgy	8,779	35.25	50.99	2.99	13.11	−9.34	10.53	22.37	42.07	125.36	18.62	9.68	1.95
		2.52	3.74	0.14	1.19	2.37	1.39	1.70	2.82	9.03	2.09	1.46	0.28
HiTec	33,251	51.27	65.11	2.79	10.64	−1.12	16.58	32.78	61.66	172.81	25.13	4.82	1.04
		3.08	5.32	0.12	0.99	0.90	0.76	1.52	3.36	13.89	1.46	0.34	0.09
Telcm	3,937	43.81	58.63	2.76	11.28	−2.04	14.28	25.15	50.23	161.90	29.28	4.50	0.79
		4.47	7.27	0.17	1.42	1.81	0.82	2.01	5.25	22.39	3.79	0.54	0.17
Shops	22,081	36.40	51.83	3.66	20.16	−3.13	12.18	23.61	42.57	115.47	24.58	5.57	1.41
		1.80	3.99	0.22	2.31	0.89	0.38	0.72	1.89	7.45	1.68	0.35	0.15
Hlth	15,987	47.96	65.88	2.81	10.31	−0.88	13.93	28.10	54.75	176.48	19.95	4.54	1.23
		2.89	5.88	0.13	0.99	1.15	0.45	1.04	3.10	14.44	1.78	0.43	0.15
Utils	7,951	13.99	19.68	4.06	33.83	1.46	7.61	10.97	15.28	31.74	32.44	2.94	0.78
		0.52	2.60	0.52	6.47	0.81	0.26	0.33	0.47	2.00	4.18	0.50	0.12
Other	22,958	40.96	64.82	3.16	13.41	−8.62	9.53	23.50	46.99	153.22	25.84	7.86	2.35
		2.66	5.54	0.14	1.14	0.98	0.55	1.10	2.48	13.08	1.54	0.35	0.19

Figure A1 : The Cross-sectional Distribution of Gross Annual Investment Rates, The Impact of Large M&As, Alternative Investment Measure As CAPX Minus SPPE, 1962–2018

In Panel A, we exclude financials, firms with negative book equity, and firm-year observations with nonpositive total assets, net property, plant, and equipment, or sales, but impose no restriction on M&As. Investment is CAPX minus SPPE (zero if missing). The sample is from 1962 to 2018, with 171,787 firm-year observations. In Panel B, we exclude financials, firms with negative book equity, and firm-year observations with nonpositive total assets, net property, plant, and equipment, or sales. We also exclude firms with sizeable M&As with the target assets at least 15% of the acquirer assets. The sample is from 1962 to 2018, with 164,723 firm-year observations. We measure M&As as the maximum of reported acquisitions from Compustat annual item AQC and the total value of all acquisitions in a given fiscal year from the Securities Data Company (SDC) dataset. When no M&A activities are reported in either database, we set the amount of M&As to zero. Capital, K_{it}, is net property, plant, and equipment (Compustat annual item PPENT). The depreciation rate, δ_{it}, is the amount of depreciation and amortization (item DP) minus the amortization of intangibles (item AM, zero if missing), scaled by item PPENT. The gross investment rate, I_{it}/K_{it}, is the net investment rate, $(K_{it+1} - K_{it})/K_{it}$, plus the depreciation rate, δ_{it}. We winsorize the gross investment rates at the 1%–99% level for the pooled firm-year observations of the fiscal years ending in a given calendar year.

Panel A: Investment as CAPX minus SPPE, 171,787 firm-year observations



Panel B: The no-large-M&A sample, 164,723 firm-year observations

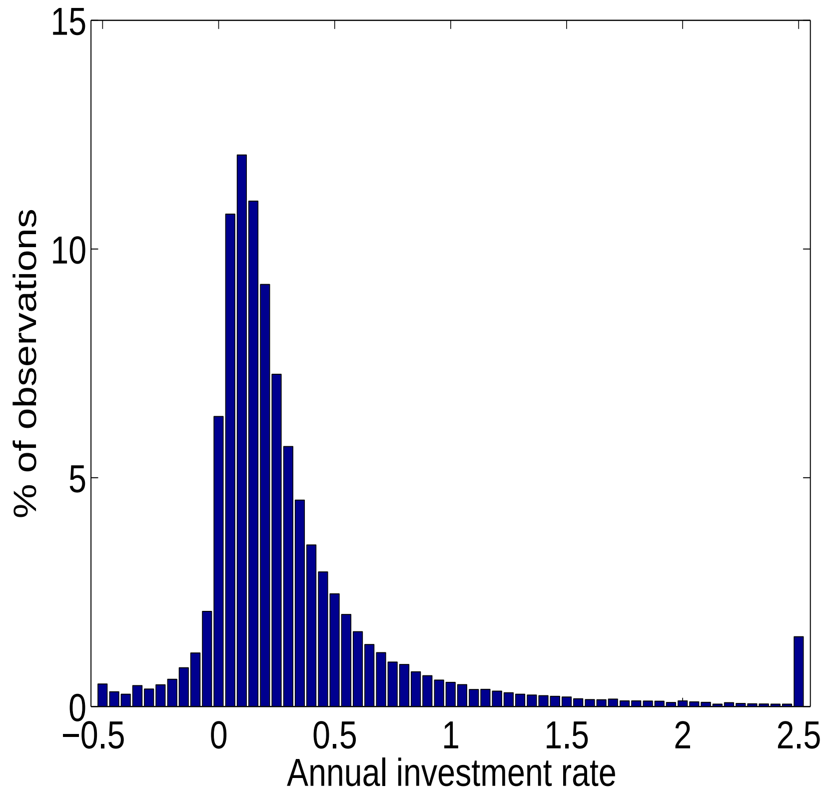


Figure A2 : The Cross-sectional Distribution of Gross Annual Investment Rates, Small versus Big Firms, 1962–2018

We exclude financials, firms with negative book equity, and firm-year observations with nonpositive total assets, net property, plant, and equipment, or sales. Capital, K_{it}, is net property, plant, and equipment (Compustat annual item PPENT). The depreciation rate, δ_{it}, is the amount of depreciation and amortization (item DP) minus the amortization of intangibles (item AM, zero if missing), scaled by item PPENT. The gross investment rate, I_{it}/K_{it}, is the net investment rate, $(K_{it+1} - K_{it})/K_{it}$, plus the depreciation rate, δ_{it}. Each year we winsorize the gross investment rates in the full sample at the 1%–99% level for the pooled firm-year observations of the fiscal years ending in a given calendar year. We then split the sample into two, small and big, based on the NYSE median of the beginning-of-fiscal-year market equity.

Panel A: The small-firm sample, 134,937 firm-year observations

Panel B: The big-firm sample, 37,936 firm-year observations

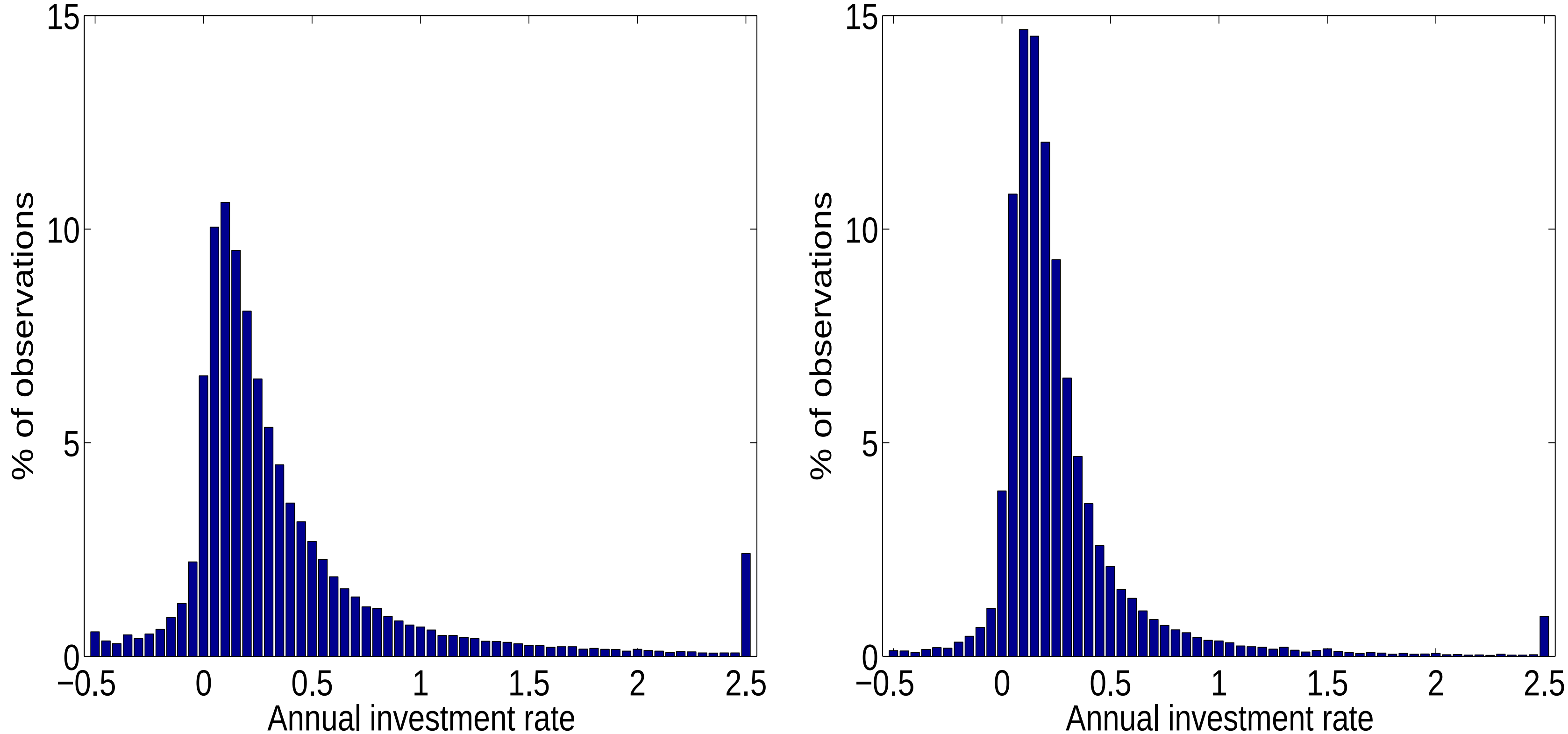
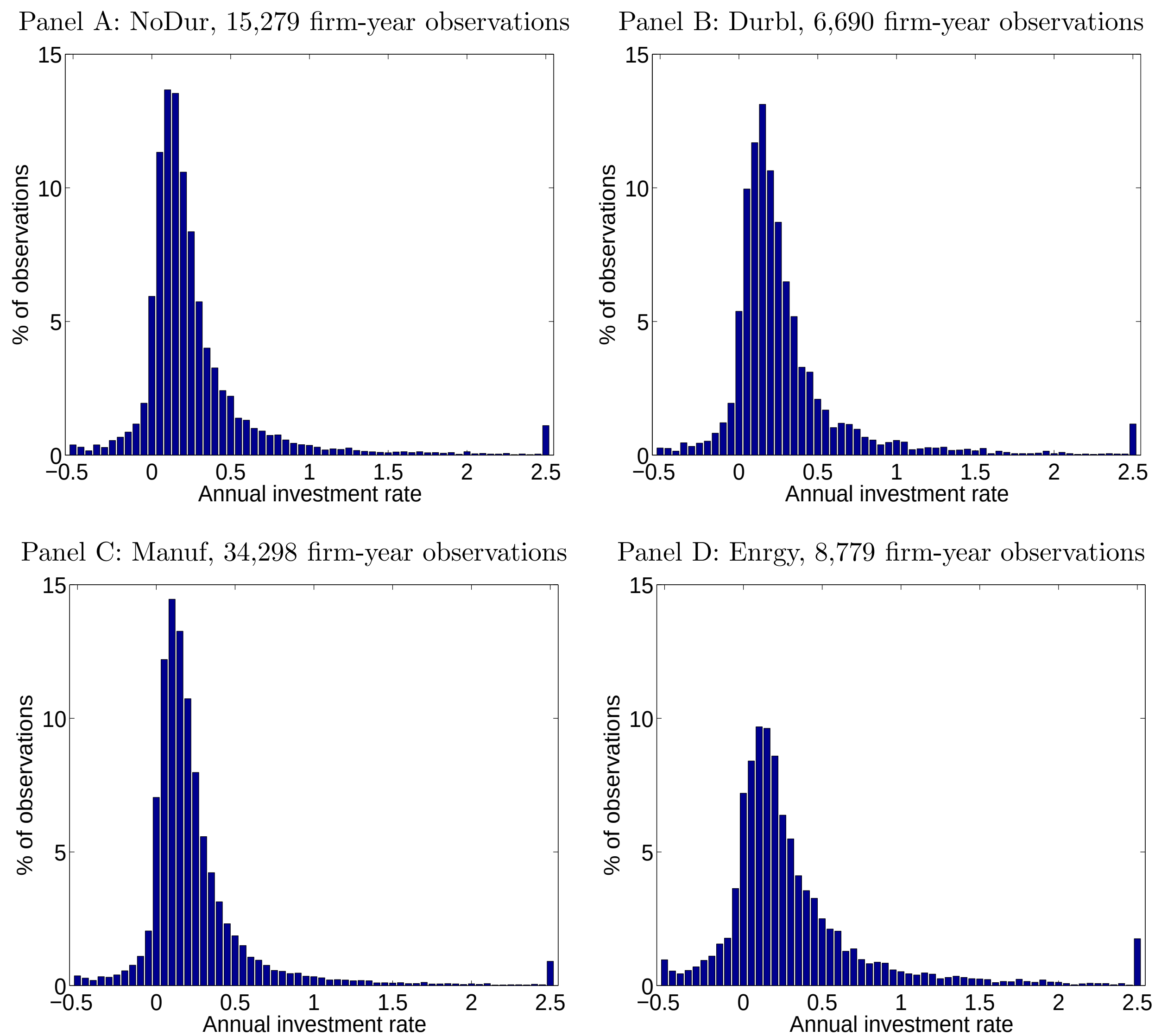
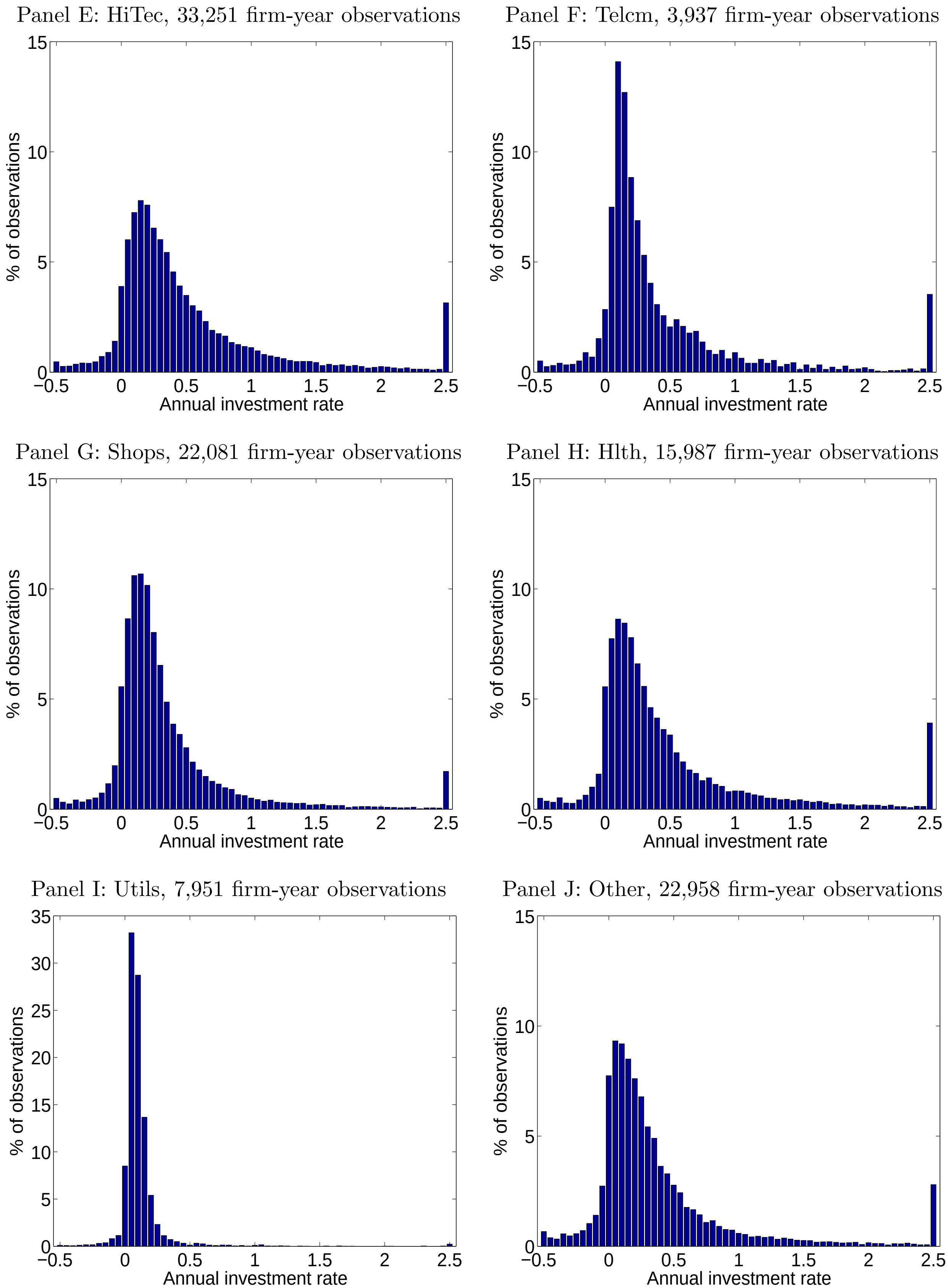


Figure A3 : The Cross-sectional Distribution of Gross Annual Investment Rates, Ten Industries, 1962–2018

We exclude financials, firms with negative book equity, and firm-year observations with nonpositive total assets, net property, plant, and equipment, or sales. Capital, K_{it}, is net property, plant, and equipment (Compustat annual item PPENT). The depreciation rate, δ_{it}, is the amount of depreciation and amortization (item DP) minus the amortization of intangibles (item AM, zero if missing), scaled by item PPENT. The gross investment rate, I_{it}/K_{it}, is the net investment rate, $(K_{it+1} - K_{it})/K_{it}$, plus the depreciation rate, δ_{it}. Each year we winsorize the gross investment rates in the full sample at the 1%–99% level for the pooled firm-year observations of the fiscal years ending in a given calendar year. We then split the sample into ten Fama-French industries, including consumer nondurables (NoDur), consumer durables (Durbl), manufacturing (Manuf), energy (Enrgy), high tech (HiTec), telecommunication (Telcm), shops (Shops), health care (Hlth), utilities (Utils), and others (Other). Appendix **??** classifies the industries based on SIC codes.




Panel E: HiTec, 33,251 firm-year observations
Panel F: Telcm, 3,937 firm-year observations
Panel G: Shops, 22,081 firm-year observations
Panel H: Hlth, 15,987 firm-year observations
Panel I: Utils, 7,951 firm-year observations
Panel J: Other, 22,958 firm-year observations
% of observations
Annual investment rate