Capacity Choice, Momentum and Long-term Reversals*

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Abstract

A real options-based firm valuation model suggests that momentum and long-term reversal effects in stock returns arise through an excess capacity channel linked to expected returns. The model predicts that momentum losers have mild excess capacity, but fully utilize their capacity, resulting in expected returns that are lower than for momentum winners. In contrast, long-term losers have higher excess capacity and a less than full capacity utilization, resulting in expected returns that are higher than for long-term winners. Cross-sectional and time-series tests show that a fundamentals-based proxy for excess capacity strongly conditions the momentum and long-term reversal effects in ways consistent with the model's testable implications.

Keywords Irreversible investment; real options; capacity choice; momentum effect; long-term reversal effect; stock returns;

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1 Introduction

Prior research has found that asset returns measured over the recent past (e.g., the last year) are positively correlated with future returns, a phenomenon referred to as the momentum effect (Jegadeesh and Titman (1993, 2001)). But past returns measured over longer-term intervals are negatively correlated with future returns, a phenomenon referred to as the long-term reversal effect (De Bondt and Thaler (1985, 1987)). Although momentum and long-term reversal effects are stable across assets and countries (see, e.g., Rouwenhorst (1998), Griffin et al. (2003), Asness et al. (2009)), they have to date not been jointly explained by rational asset pricing models.

We contribute to the literature in two ways. First, our theory shows that momentum and long-term reversal effects can reflect cross-sectional variations in expected stock returns induced through an excess capacity channel, where excess capacity is defined as installed capacity minus ex-ante optimal capacity. Second, our empirical work shows that prior stock returns proxy for changes in excess capacity, and therefore for changes in expected stock returns. A fundamentals-based estimate of excess capacity conditions momentum and long-term reversal effects both in the cross-section and the time-series of U.S. stock returns, in directions predicted by our theory.

Our intuition is as follows. Assume that product demand risk is the only source of uncertainty that firms face and that firms' investment decisions are largely irreversible. In this setup, momentum winners (long-term winners) have experienced good news about product demand over the short-term (long-term) past and have lower excess capacity relative to momentum losers (long-term losers) on average. Low excess capacity translates into a moderate level of systematic risk because future demand shocks affect both price and capital investment: If demand increases further for winners, cash flows increase because products sell at higher prices and also because firms invest in new capital to increase output. However, if demand falls, cash flows decrease because products sell at lower prices, but production levels are not adversely affected. As a result, winners are very sensitive to demand shocks on the upside, but less sensitive on the downside.

Compare momentum winners with momentum losers. Momentum losers have experienced bad news about product demand over the recent past and hence have mild excess capacity on average. But such firms still fully utilize capacity and thus have lower systematic risk than momentum winners because future demand shocks affect price but do not affect production levels: If demand picks up, momentum winners realize higher cash flows because they sell *the same amount of output* at higher prices. If demand falls further, they realize lower cash flows because they sell *the same amount of output* at lower prices. Finally compare long-term winners with long-term losers. Long-term losers have experienced bad news about product demand over a much longer past period and thus are more likely to suffer from significant excess capacity and capacity under-utilization. Long-term losers have higher systematic risk than long-term winners because future demand shocks affect both the price at which these firms sell their output, but also their production levels: If demand picks up, long-term losers realize higher cash flows because they sell *more output* at higher prices. If demand falls further, they realize lower cash flows because they sell *less output* at lower prices.

We confirm our intuition using Pindyck's (1988) model of firm valuation under irreversible investments and demand uncertainty. This author values the firm as a portfolio comprising two components: (i) the value-weighted portfolio of operating options that can be used to produce output (assets-in-place), and (ii) the value-weighted portfolio of options to install new capacity (growth options). Optimal investment dynamics respond to changes in demand. However, because investments are irreversible, options to defer investments are valuable, and new investment is not triggered continuously as demand increases. In contrast, when demand decreases and installed capacity rises above the currently optimal level of capacity, the firm builds up excess capacity. In choosing the profit-maximizing production level, it can be optimal to operate below full capacity if demand falls sufficiently, in which case the firm has both excess capacity and capacity under-utilization. However, excess capacity does not necessarily imply capacity under-utilization.

Pindyck (1988) models both production options and growth options as perpetual American calls, implying that the expected return on each type of option depends on the option elasticity and the systematic risk of the underlying asset, a mimicking portfolio on demand. While the elasticities of growth options are independent of demand (Shackleton and Wojakowski (2002)), the elasticities of production options are negatively correlated with demand, implying a positive relationship between the expected return on production options and excess capacity. The expected return of the firm is a value-weighted average of the expected returns of the production options and the growth options. Because the value of a production option (unit of capacity) is higher than the value of the equivalent growth option, the model produces a U-shaped relationship between a firm's expected return and demand, and thus a U-shaped relationship between the expected return and excess capacity.

The stylized example in Table 1 helps to clarify the intuition behind the U-shaped relationship. The firms in the example own three assets, Asset 1, 2, and 3, each in the form of either an asset-in-place or a growth option. If installed as an asset-in-place, Assets 1, 2, and 3 can be used to produce the first, second, and third output units, respectively, with costs increasing according to a convex cost function. The example obeys the following implications of Pindyck's (1988) model: (i) elasticities of production options increase over the output units; (ii) while the elasticities of the growth options are constant, they are higher than those of the utilized assets-in-place, but equal to those of the idle assets-in-place; (iii) the value of a production option is higher than that of the equivalent growth option, but the values of both decline over the output units; and (iv) the expected firm return is a value-weighted average of the elasticities of the assets multiplied by 0.08.[1]

Assume optimal capacity is equal to one asset-in-place, so that Firm A's capacity is optimal. In contrast, Firm B also installed the second unit of capacity, so that the first growth option of Firm A

[1]For simplicity, but without loss of generality, we assume here that the expected excess return of the underlying asset is 8%.

is replaced by a utilized asset-in-place with lower elasticity (2.50 vs. 6.00) and higher market value (5.00 vs. 4.00). Although it faces the same demand as Firm A, the lower elasticity of the asset-in-place on the second output unit implies that Firm B has a lower expected return than Firm A (17% vs. 25%). Finally, Firm C installed all three capacity units. Facing the same demand as Firms A and B, it finds it optimal to only utilize the first two capacity units, leaving the third idle. The idle capacity unit has the same elasticity as the growth option on the same output unit, but its market value is higher. Thus, Firm C has a higher expected return than Firm B (20% vs. 17%). In sum, utilized excess capacity pushes down the expected return; idle excess capacity increases it.

Assuming momentum winners have low excess capacity, while momentum losers have moderate excess capacity, a cross-sectional implication of Pindyck's (1988) model is that momentum winners have higher expected returns than momentum losers. Assuming long-term winners have even lower excess capacity than momentum winners, while long-term losers have higher excess capacity than momentum losers, a further cross-sectional implication is that long-term losers have higher expected returns than long-term winners if excess capacity is sufficiently high. Because excess capacity systematically increases in recessions, a time-series implication of the model is that momentum effects decrease, and long-term reversal effects increase, with aggregate excess capacity. The last implication can explain why momentum effects are pro-cyclical, and long-term reversal effects are counter-cyclical (Chan et al. (1996), Griffin et al. (2003), Cooper et al. (2004)).

The above implications continue to hold when we allow for some mild investment irreversibility. However, when the cost of investment reversibility falls sufficiently, the excess capacity-expected return relationship becomes monotonically negative. This is consistent with results reported in Hackbarth and Johnson (2012), and it implies that firms with sufficiently reversible investments should not produce long-term reversal effects.

In our empirical work, we develop a new fundamentals-based proxy for firm-level excess capacity. Our strategy to estimate excess capacity is grounded in practical financial analysis, in which operating efficiency is often assessed with reference to the asset turnover ratio (i.e., sales-to-total assets). We use stochastic frontier analysis (SFA) of total assets to estimate optimal capacity for each firm each month (Aigner et al. (1977), Meeusen and van den Broeck (1977), Hunt-McCool et al. (1996), Habib and Ljungqvist (2005)). The dependent variable in the SFA is total assets scaled by sales (to alleviate heterogeneity), and we assume that optimal capacity is linear in factors capturing demand, production costs, systematic risk, and volatility. The SFA estimates a firm's hypothetical optimal capacity equivalent to the best-performing industry peers, holding other factors constant. We calculate the excess capacity proxy as the difference between observed total assets and estimated optimal total assets. To validate the excess capacity proxy, we show that measures of average excess capacity estimated using our methodology are highly correlated with an economy-wide capacity under-utilization index estimated from surveys of manufacturing firms.

Initially, we condition momentum and long-term reversal premia in the cross-section of U.S. stocks on firm-month excess capacity estimates. In support of theoretical predictions, momentum returns are negatively correlated with excess capacity and only significant when excess capacity is low. For example, the mean return spread between momentum winners and losers is statistically and economically significant at 8.13% per annum for low excess capacity stocks, while for high excess capacity stocks the same spread is insignificant at -1.94%. In contrast, long-term reversal returns are positively correlated with excess capacity. The mean return spread between long-term losers and winners is insignificant at 2.37% per annum for low excess capacity stocks, while for high excess capacity stocks the same mean return spread is a highly significant 17.13%.

Finally, we study the time-series implications of Pindyck's (1988) model. To achieve this goal, we run time-series regressions of momentum and long-term reversal returns on aggregate excess capacity and standard macroeconomic controls. Our results show that an aggregate excess capacity measure based on firm-specific SFA estimates is the strongest predictor of momentum and long-term reversal returns, and that a high level of aggregate excess capacity significantly decreases momentum profits, but significantly increases long-term reversal profits.

In robustness tests, we analyze the possibility of replacing the SFA-based excess capacity proxy with a simpler indirect proxy. Here we exploit the intuition that firms with excess capacity will not invest into new capacity until demand recovers to the point at which new investment becomes optimal again. Consistent with Pindyck's (1988) model, we predict that higher levels of excess capacity are associated with a lower chance of investing into new capacity. Motivated by this insight, we define our indirect excess capacity proxy as the inverse of the probability of a positive asset growth over the next year, estimated using LOGIT regressions. Replacing the SFA estimate with this indirect proxy, we obtain results that are virtually identical to our main results.

The remainder of this paper is organized as follows. Section 2 reviews the literature. Section 3 introduces the Pindyck (1988) model and derives our predictions. Section 4 provides our empirical results, and Section 5 summarizes and concludes. Proofs are in the appendix.

2 Links to prior literature

2.1. Theoretical literature

Several theoretical studies have used neoclassical or real options investment models to explain characteristic anomalies, including Carlson et al. (2004), Zhang (2005), Cooper (2006), Sagi and Seasholes (2007), Aguerrevere (2009), and Liu and Zhang (2011). However, none of these studies, except Liu and Zhang (2011), explicitly consider momentum *and* long-term reversal effects.[2]

[2] Other models that can rationalize characteristic anomalies include Berk et al. (1999) and Gomes et al. (2003). These models are of great historical importance in the evolution of the literature, but they assume that growth opportunities arise independent of a firm's economic conditions. As Zhang (2005, p.70) states, "this is counterfactual."

Cooper (2006) analyzes the effect of excess capacity on expected returns, but his model assumes that firms produce at the installed capacity level. Thus, Cooper (2006) finds a positive relationship between excess capacity and expected return, while we find a U-shaped relationship. Furthermore, Cooper (2006) shows that the book-to-market ratio can act as a state variable that captures excess capacity. Given that the book-to-market ratio depends negatively on past returns, the positive relationship between excess capacity and expected returns established by Cooper (2006) is consistent with the long-term reversal effect, but not with the momentum effect.

Our analysis is similar to Aguerrevere's (2009) analysis in that both studies are based on Pindyck's (1988) model. Aguerrevere (2009) documents that the riskiness of assets-in-place increases as product demand decreases. Our work yields consistent conclusions, although we ignore the degree of industry competition. We also differ in that we examine how excess capacity helps to explain momentum and long-term reversal effects. Aguerrevere (2009) focuses exclusively on how the interaction of excess capacity and product market competition determines expected returns.

Using a neoclassical investment model, Liu and Zhang (2011) show that momentum and long-term reversal effects can be linked to the model's implied investment optimality conditions. At the time of portfolio formation, momentum winners have higher expected returns than losers due to higher growth in the investment-to-capital ratio and a higher sales-to-capital ratio. However, their model cannot account for counter-cyclical momentum profits. It also suggests that the same stocks drive both the momentum and long-term reversal effects, which contradicts evidence in Conrad and Yavuz (2012). Further, their approach does not identify the channels through which risk affects the cost of equity. Instead, they back out the discount rate from investment decisions, and the discount rate in turn depends on profitability. In contrast, our model renders investment, capacity utilization, and systematic risk jointly dependent on stochastic demand. Systematic risk is thus endogenous and depends on ex-ante optimally chosen capacity and ex-post optimally chosen output.[3]

Our work is somewhat related to several other papers. For example, Sagi and Seasholes (2007) model the firm as a portfolio of two assets, a low risk asset (e.g., an asset-in-place) and a high risk asset (e.g., a growth opportunity). News reflected in returns changes the value weights of the assets, leading expected returns to depend positively on past returns. Our model includes a similar mechanism, but we also predict negative dependence between past return and expected return if long-run past returns are sufficiently low and excess capacity is sufficiently large. Hence, in contrast to Sagi and Seasholes (2007), we also offer a rationale for long-term reversal effects. Carlson et al. (2004) seek to explain the size and book-to-market effects using a model with fixed production costs, fixed and variable capital adjustment costs, and the option to shut down installed capacity. Their model predicts that size captures the importance of a firm's growth options and book-to-market its operating leverage. Our model differs in that it does not feature fixed costs, and therefore does not rely on operating leverage effects. Finally, Zhang (2005) uses an industry equilibrium model with an asymmetric convex capacity adjustment cost function and fixed production costs. In his model, value stocks slowly divest capital upon receiving bad news and thus do not efficiently smooth profits using their investment policies. This behavior leads to high systematic risk.

2.2. Empirical literature

Only a few studies test the predictions of the above models (Dijk (2011)). An early exception is Ball and Kothari (1989), who show that long-term losers (winners) experience large increases (decreases) in market betas before the portfolio formation date. Our analysis suggests a channel through which these risk changes occur. Anderson and Garcia-Feijóo (2006) report that the capital expendi-

[3]Interestingly, a key construct in our model that determines systematic risk is the asset turnover ratio (sales-to-capital). This variable is vital to the classic investment model because of its linear relationship to the marginal productivity of capital in a Cobb-Douglas production economy.

tures of growth firms are larger than those of value firms. Assuming that growth firms invest mostly in projects with low systematic risk, this result supports predictions derived from Berk et al.'s (1999) model. Garcia-Feijóo and Jorgensen (2010) report that the book-to-market ratio captures operating exposure, measured using the approaches of Mandelker and Rhee (1984) and O'Brien and Vanderheiden (1987), or accounting proxies. This is consistent with the model prediction that book-to-market captures cross-sectional variations in operating leverage (Carlson et al. (2004)). Finally, Liu and Zhang (2011) show that stock returns implied from a neoclassical investment model produce momentum and long-term reversal effects. Our paper complements these studies by establishing a channel linking short and long-horizon returns to expected returns via excess capacity.

3 Theoretical model

3.1. Setup

Pindyck (1988) studies a firm producing a single product, with demand for this product, θ, evolving according to Geometric Brownian motion with constant drift (α) and volatility (σ). Assuming (initially) that investments are irreversible, the firm decides at each point in time whether to expand capacity and then how much output to produce. Thus, firm value, W, can be decomposed as:

$$W = \int_0^K \Delta V(v;\theta)dv + \int_K^\infty \Delta F(v;\theta)dv, \tag{1}$$

where the first term on the right-hand side represents the component of firm value due to assets-in-place, and the second term represents the component of firm value due to growth opportunities (i.e., options to install new capacity). We denote the number of (infinitesimally small) production units in place as K, $\Delta V(v;\theta)$ is the value of the capacity unit producing the vth unit of output, and $\Delta F(v;\theta)$ is the value of an option to install new capacity able to produce the vth unit of output. The unit costs of installing new capacity are constant and equal to k. While each production unit can produce one unit of output at increasing costs, production can be costlessly shut down at each point in time.

Optimal capacity fulfills the following equality:

$$\Delta V(K^*;\theta) = k + \Delta F(K^*;\theta). \tag{2}$$

Intuitively, optimal capacity K^* equates the value of the marginal production unit with its cost, composed of the installation cost and the cost of sacrificing the growth option.

The demand function is given by $P = \theta(t) - \gamma Q$, where P is the unit price of output, γ is the elasticity of demand (a parameter), and Q is the quantity of output produced (a choice variable). Operating costs, $C(Q)$, are given by $c_1 Q + (1/2)c_2 Q^2$, where c_1 and c_2 are cost function parameters. To bound firm size, we require $\gamma > 0$ or $c_2 > 0$. The firm determines optimal output by maximizing profits, given by $PQ - c_1 Q - (1/2)c_2 Q^2$. To use contingent claims analysis, we require the existence of a traded asset perfectly correlated with demand, θ. Let μ denote the expected return of this traded asset, and δ denote the spread between its expected return and the drift rate of the stochastic process (i.e., $\delta \equiv \mu - \alpha$). A necessary condition for firms to invest is $\delta > 0$.

Under these assumptions, Pindyck (1988) shows that the value of the production unit manufacturing the Kth output unit, $\Delta V(K)$, is equal to:

$$\Delta V(K) = \begin{cases} b_1 \theta^{\beta_1}; & \theta \leq (2\gamma + c_2)K + c_1 \\ b_2 \theta^{\beta_2} + \theta/\delta - [(2\gamma + c_2)K + c_1]/r; & \theta \geq (2\gamma + c_2)K + c_1, \end{cases} \tag{3}$$

where r is the risk-free rate of return, and β_1, β_2, b_1, and b_2 are given in Appendix A. If $\theta \leq (2\gamma + c_2)K + c_1$, the firm shuts down the production unit, implying that its value derives from the possibility of re-opening it in the future. Else, the firm uses the production unit, implying that its value derives from using the production unit in perpetuity plus the value of the option to shut down production.

Pindyck (1988) also shows that the value of the option to install this production unit, $\Delta F(K)$, is given by:

$$\Delta F(K) = \begin{cases} a\theta^{\beta_1}; & \theta \leq \theta^*(K) \\ \Delta V(K) - k; & \theta \geq \theta^*(K), \end{cases} \tag{4}$$

where a is given in Appendix A. If $\theta \leq \theta^*(K)$, the firm waits to exercise the growth option, implying that its value derives from possible future exercise. Else, the firm immediately installs the production unit, implying that its value is equal to that of the production unit minus the installation costs, k.

The optimal investment threshold, θ^*, satisfies the following equation:

$$\frac{b_2(\beta_1 - \beta_2)}{\beta_1}(\theta^*)^{\beta_2} + \frac{(\beta_1 - 1)}{\delta\beta_1}\theta^* - \frac{(2\gamma + c_2)K + c_1}{r} - k = 0, \tag{5}$$

which can be re-written as a function of the optimal capacity level K^*.

3.2. Main results

Using the results in Cox and Rubinstein (1985) or Carlson et al. (2004), the expected excess return of the production unit producing the νth unit of output is given by:

$$E[r_{\Delta V(v;\theta)}] - r = \Omega_{V(v;\theta)}(\mu - r), \tag{6}$$

where $\Omega_{V(v;\theta)}$ is the elasticity of the production unit, $(\partial \Delta V(v;\theta)/\partial\theta) \cdot (\theta/\Delta V(v;\theta))$. If $\theta \leq (2\gamma + c_2)K + c_1$ and the firm optimally shuts down the production unit, this elasticity is equal to β_1 (a constant). Else, the elasticity is equal to $(b_2\beta_2\theta^{\beta_2} + \theta/\delta)/\Delta V(v;\theta)$.

The expected excess return of the growth option on the production unit producing the vth output unit is:

$$E[r_{\Delta F(v;\theta)}] - r = \Omega_{F(v;\theta)}(\mu - r), \tag{7}$$

where $\Omega_{F(v;\theta)}$ is the elasticity of the growth option, $(\partial \Delta F(v;\theta)/\partial\theta)\cdot(\theta/\Delta F(v;\theta))$. If $\theta \leq \theta^*(K)$ and the growth option is not immediately exercised, this elasticity equals β_1 (a constant).

Without loss of generality, we set $(\mu - r)$ equal to one in the remainder, in this way preventing dispersion in expected returns due to demand risk dispersion.

Because the firm is a portfolio consisting of assets-in-place and growth options, its expected excess return is given by the value-weighted average taken over the expected excess returns of the two types of assets in the portfolio:

$$\begin{aligned} E[r_A] - r &= \int_0^K \frac{\Delta V(v;\theta)}{W}\left(E[r_{\Delta V(v;\theta)}] - r\right)dv + \int_K^\infty \frac{\Delta F(v;\theta)}{W}\left(E[r_{\Delta F(v;\theta)}] - r\right)dv && (8) \\ &= \int_0^K \frac{\Delta V(v;\theta)}{W}\Omega_{V(v;\theta)}dv + \int_K^\infty \frac{\Delta F(v;\theta)}{W}\Omega_{F(v;\theta)}dv. && (9) \end{aligned}$$

Consider a firm that has optimally shut down some fraction of its excess capacity (i.e., the firm shuts down all production units for which $K \geq (\theta - c_1)/(2\gamma + c_2)$; see the system of equations in (3)). Using Equation (9), the expected excess return of this firm is given by:

$$E[r_A] - r = \frac{1}{W}\left(\int_0^{\frac{\theta - c_1}{2\gamma + c_2}}(b_2\beta_2\theta^{\beta_2} + \theta/\delta)dv + \beta_1\int_{\frac{\theta - c_1}{2\gamma + c_2}}^K \Delta V(v,\theta)dv + \beta_1\int_K^\infty \Delta F(v;\theta)dv\right). \tag{10}$$

The partial derivative of this expected excess return with respect to capacity, K, is:

$$\begin{aligned}\frac{\partial E[r_A]-r}{\partial K} &= \frac{1}{W^2}\Bigg[\beta_1(\Delta V(K,\theta)-\Delta F(K,\theta))\cdot W-(\Delta V(K,\theta)-\Delta F(K,\theta)) \\ &\quad\cdot\left(\int_0^{\frac{\theta-c_1}{2\gamma+c_2}}(b_2\beta_2\theta^{\beta_2}+\theta/\delta)dv+\beta_1\int_{\frac{\theta-c_1}{2\gamma+c_2}}^{K}\Delta V(v,\theta)dv+\beta_1\int_K^{\infty}\Delta F(v;\theta)dv\right)\Bigg]\end{aligned} \tag{11}$$

or, equivalently:

$$\frac{\partial E[r_A]-r}{\partial K}=\left(\frac{\Delta V(K,\theta)}{W}-\frac{\Delta F(K,\theta)}{W}\right)\left(\beta_1-(E[r_A]-r)\right). \tag{12}$$

We use the following two lemmas to sign the partial derivative:

Lemma 1: *The strict ordering of functions* $\Delta V(\theta)$ *and* $\Delta F(\theta)$*, given by:*

$$\Delta V(\theta)>\Delta F(\theta),$$

holds over the entire domain of θ.

Proof: *See Appendix B.*

The inequality suggests that the value of an unexercised growth option is bounded from above by the value of the underlying production unit. Intuitively, this holds because (i) the production unit yields higher payoffs than the growth option (if it is used before exercise of the growth option), or payoffs equal to the growth option (if it is not used before exercise of the growth option, or after exercise), and (ii) the firm must pay the installation costs upon exercise of the growth option.

Lemma 2: *Over the region* $\theta=\{(2\gamma+c_2)K+c_1,\infty\}$*, the elasticity of an idle production option or an unexercised growth option,* β_1*, is larger than the elasticity of a non-idle production option,*

$(b_2\beta_2\theta^{\beta_2} + \theta/\delta)/\Delta V(K,\theta)$.

Proof: *See Appendix C.*

We can now sign the partial derivative in Equation (12):

Proposition 1: *If $K \geq (\theta - c_1)/(2\gamma + c_2)$, the partial derivative of the expected excess return with respect to capacity is positive, that is:*

$$\frac{\partial E[r_A] - r}{\partial K} = \left(\frac{\Delta V(K,\theta)}{W} - \frac{\Delta F(K,\theta)}{W}\right)\left(\beta_1 - (E[r_A] - r)\right) > 0.$$

Proof: *By Lemma 1, $(\Delta V(K,\theta) - \Delta F(K,\theta)) > 0$. Equation (9) shows that $(E[r_A] - r)$ is the value-weighted average elasticity of the firm's options. Lemma 2 suggests that β_1 is the maximum elasticity of both the production options and the growth options, implying that $(\beta_1 - (E[r_A] - r)) > 0$.*

Intuitively, the sign of the partial derivative is positive because we swap one growth option with an elasticity of β_1 for a production option with the same elasticity. Nevertheless, because the production option is worth more than the growth option, the weights used to compute the expected excess return are now higher for options with elasticities of β_1 and lower for those with lower elasticities.

Figure 1 illustrates these two effects. When θ is below unity, the firm optimally decides to not use the production option shown in the graph, and so it has an elasticity equal to that of the corresponding (i.e., on the same output unit) growth option. However, the production option has a higher market value than the corresponding growth option, especially when it is just out-of-the-money.

Next consider a firm that exhibits excess capacity, but that is still producing at full capacity (i.e., a firm whose capacity fulfills the inequality $K^* < K \leq (\theta - c_1)/(2\gamma + c_2)$). This firm's expected excess return is given by:

$$E[r_A]-r=\frac{1}{W}\left(\beta_2\theta^{\beta_2}\int_0^K b_2 dv+\theta/\delta\int_0^K dv+\beta_1\int_K^\infty \Delta F(v;\theta)dv\right). \tag{13}$$

The partial derivative of this expression with respect to capacity, K, equals:

$$\begin{aligned}\frac{\partial E[r_A]-r}{\partial K} &= \frac{1}{W^2}\Bigg[\left(b_2(K)\beta_2\theta^{\beta_2}+\theta/\delta-\beta_1\Delta F(K,\theta)\right)\cdot W-\left(\Delta V(K,\theta)-\Delta F(K,\theta)\right) \\ &\quad \cdot\left(\beta_2\theta^{\beta_2}\int_0^K b_2 dv+\theta/\delta\int_0^K dv+\beta_1\int_K^\infty \Delta F(v;\theta)dv\right)\Bigg],\end{aligned} \tag{14}$$

or, equivalently:

$$\frac{\partial E[r_A]-r}{\partial K}=\frac{\Delta V(K,\theta)}{W}\left(\frac{b_2(K)\beta_2\theta^{\beta_2}+\theta/\delta}{\Delta V(K,\theta)}-(E[r_A]-r)\right)-\frac{\Delta F(K,\theta)}{W}\left(\beta_1-(E[r_A]-r)\right). \tag{15}$$

A sufficient condition for Equality (15) to be negative is that the elasticity of the marginal production option, $(b_2(K)\beta_2\theta^{\beta_2}+\theta/\delta)/\Delta V(K,\theta)$, is below the value-weighted average elasticity of the production and growth options, $(E[r_A]-r)$, which occurs predominantly when excess capacity is very low. The intuition behind the potentially negative relationship is that swapping the marginal growth option for the marginal production option now has two opposing sign effects on the expected return. First, we exchange an option with a higher elasticity for one with a lower elasticity $(\beta_1 > (b_2(K)\beta_2\theta^{\beta_2}+\theta/\delta)/\Delta V(K,\theta))$, which decreases the expected excess return. However, second, we swap a less valuable option for a more valuable option $(\Delta V(K,\theta) > \Delta F(K,\theta))$, tilting the weights used to compute the expected excess return toward options with higher elasticities and increasing the expected excess return. When excess capacity is low enough, the first effect dominates, implying that the expected excess return decreases with excess capacity.

We again summarize these effects in Figure 1. When θ is between the optimal production threshold and the optimal expansion threshold (one and two), say at θ_1, the elasticity of the production option is below that of the growth option. However, the market value of the production option is above that of the growth option. When the growth option is close to being in-the-money (i.e., θ close to θ^*), as is the case at θ_1, the difference in elasticities is far greater in magnitude than the difference in the market values. As a result, it is exactly in this region in which a higher excess capacity, induced through a lower demand, pushes down the expected return.

3.3. Reversible investment

Although Pindyck (1988) assumes that investment decisions are completely irreversible, in reality most should be reversible at some costs. To explore how investment reversibility affects our results, we next allow firms to dispose of existing capacity at a unit selling price of d. The spread between the installation cost k and the selling price d is the deadweight cost of reversing an investment, with a wider spread signalling less reversibility. In Appendix D, we derive the values of the options in this augmented setup. Using these in combination with the options' elasticities, we derive a firm's expected returns and capacity utilizations for different levels of investment reversibility.

Figure 2 plots the expected excess return (on the left y-axis) and capacity utilization (on the right y-axis) against installed capacity (on the x-axis). To allow for variations in investment reversibility, we use a installation cost k of 10, but a selling price d of either 0.00, 1.00, 2.50, or 5.00. We set all other model inputs equal to the base case values used in Pindyck's (1988) calibrations.[4] The left-end points of each line (indicated by a box) denote the optimal investment threshold; the right endpoints (indicated by a star) denote the optimal divestment threshold.

When investments are relatively costly to reverse (e.g., $d < 5$), the relationship between expected

[4]In particular, we set demand, θ, to unity. The drift, α, and volatility, σ, of the stochastic process determining demand are 0.05 and 0.10, respectively. We choose an elasticity of demand, γ, of 0.50 and set both cost function parameters, c_1 and c_2, to zero. The unit cost of capital, k, is ten. The demand risk premium (that is, the expected return of the asset that is perfectly correlated with demand, μ) is 0.10, and the risk-free rate, r, is 0.04.

return and excess capacity is initially U-shaped. However, as excess capacity increases further, the expected return starts to fall as the point at which capacity disposal is triggered approaches. In contrast, when the costs of reversing investments are lower (e.g., $d = 5$), the U-shaped relationship between the expected return and excess capacity is eliminated, and the relationship becomes monotonically negative. The changes in the excess capacity-expected return relationship arise because a production unit now consists of an option to produce and an option to divest. As excess capacity builds up, the option to produce moves further out-of-the-money, but the option to divest moves further into-the-money. At low to moderately high excess capacity levels, the option to divest is close to worthless. Thus, it has almost no effect on the excess capacity-expected return relationship. However, when excess capacity becomes substantial, the value of the option to divest starts to dominate the value of the option to produce (and this happens earlier when the selling price d is higher). When this happens, the excess capacity-expected return relationship turns negative again.

Our results echo those in Hackbarth and Johnson (2012). When the cost of reversing investments is low, they show that systematic risk slopes upward with profitability, which is negatively correlated with excess capacity in Pindyck's (1988) model. Hackbarth and Johnson (2012) correctly point out that investment reversibility may therefore be a promising method by which to explain momentum effects. However, we show that some investment irreversibility is needed to also account for long-term reversal effects within a real options framework. Our conclusions above are also consistent with the empirical results of Nyberg and Pövry (2013), who report that momentum profits are strongest among firms that have most strongly contracted their asset base over the last fiscal year, at least if we assume that these are the firms that face the lowest costs of reversing investments.

The above results have important implications for our empirical work. While the expected returns of winners should monotonically increase with the tendency of their past returns to indicate no or low excess capacity, it is not as straightforward to determine the relationship between the expected returns of long-term losers and the tendency of their past returns to signal a significant excess capacity. When investments are sufficiently irreversible, this relationship should be positive; when investments are sufficiently reversible, this relationship should be negative.

3.4. *Testable implications*

We now use Pindyck's (1988) model to derive testable implications concerning momentum and long-term reversal effects in stock returns. The channel linking past returns to expected returns exploits the following model properties: (i) changes in demand and contemporaneous changes in market values (returns) are perfectly positively correlated; and (ii) changes in demand are positively (negatively) correlated with changes in optimal capacity (excess capacity). Hence, the model establishes an endogenous link between past returns and the level of excess capacity at the end of the past return window—high past returns are associated with relatively low levels of excess capacity, while low past returns are associated with relatively high levels of excess capacity.[5] Finally, the length of the window over which past returns are measured is relevant for the information in past returns for excess capacity—returns measured over longer past periods should be associated with more extreme changes in excess capacity than those measured over shorter past periods.

More formally, we generate the following two cross-sectional hypotheses:

H1: Momentum winners have lower excess capacity than momentum losers, and the return spread between them is more positive among stocks with lower levels of excess capacity.

H2: Long-term winners have lower excess capacity than long-term losers, and the return spread between them is more negative among stocks with higher levels of excess capacity.

[5]The association is imperfect for two reasons. First, the correlation between changes in demand and changes in excess capacity is imperfect when excess capacity is zero. Second, past returns are more strongly related to changes in excess capacity than to the level of excess capacity itself because the level of excess capacity at the end of the past return window also depends on the level of excess capacity at the beginning of the past return window.

Figure 3 helps to understand these hypotheses. The figure displays the relationship between the expected return (on the y-axis) and excess capacity (on the x-axis) when investments are irreversible. The figure highlights three ranges of excess capacity: low, medium, and high. In the low region, the expected return decreases with excess capacity; in the medium region, it is ambiguously related to excess capacity; and in the high region, it increases with excess capacity. Taken literally, Figure 3 suggests that momentum effects only exist in the low excess capacity region, and long-term reversal effects only in the high one. However, the figure only shows the expected return-excess capacity relation for a single firm, defined by a specific combination of model inputs. We can easily show that variations in the model inputs can shift the bottom of the U-shape to the left or right.[6] Thus, the strongest predictions we are able to make is that momentum effects are more pronounced in the low region, and long-term reversal effects are more pronounced in the high region.

In Hypotheses H1 and H2, we abstract from the fact that firms likely differ in how reversible their investments are. We do so to avoid having to come up with a proxy for the degree of investment irreversibility—in addition to the excess capacity proxy. Despite this, independent of how reversible investments are, if there are long-term reversal effects in the data, Pindyck's (1988) model predicts them to show up in the higher excess capacity regions, and not in the lower regions.

We also generate the following time-series hypothesis:

H3: When excess capacity is systematically low, as, for example, in expansions, momentum winners (losers) are likely to have low (moderate) excess capacity, whereas in recessions momentum winners (losers) are likely to have moderate (high) excess capacity. Thus, the return

[6]We offer comparative statistics in an Online Appendix. In a nutshell, the comparative statistics show that the span of the region over which the expected return of an excess capacity firm is below the expected return of a no excess capacity increases with demand uncertainty (σ), installation costs (k), and the risk-free rate of return (r), but decreases with the demand risk premium (μ), demand elasticity (γ), and variable costs (c_1 and c_2). Assuming that momentum effects become more prevalent than long-term reversal effects with the span of this region, our comparative statistics are completely consistent with those in Sagi and Seasholes (2007), who also show that momentum profits are positively correlated with earnings uncertainty and negatively correlated with production costs.

spread between momentum winners and losers is more positive in expansions when the momentum strategy is more likely to be concentrated in the low region of Figure 3.

H4: When excess capacity is systematically high, as, for example, in recessions, long-term winners (losers) are likely to have medium to high (high) excess capacity, whereas in expansions long-term winners (losers) are likely to have low (medium) excess capacity. Thus, the return spread between long-term winners and losers is more negative in recessions when the long-term reversal strategy is more likely to be concentrated in the high region of Figure 3.

4 Empirical tests

4.1. Proxy variables

4.1.1. Past returns

Consistent with Jegadeesh and Titman (1993) and Fama and French (1996), we define the short-term (momentum) past return (MOM) as the log compounded return over months -12 to -2. We face a dilemma in deciding on how to define the long-term past return. On the one hand, most studies jointly examining momentum and long-term reversal effects define long-term past returns over a non-overlapping period that excludes the momentum return period (Grinblatt and Moskowitz (2004)). On the other hand, if we allow the definition to include the recent momentum period, this likely signals more extreme excess capacity values, and will thus be more suitable as a basis to test our hypotheses. As a compromise, we employ two definitions for the long-term past return, the log compounded return over months -13 to -36 (LTR), and an alternative, the log compounded return over months -2 to -36 (MOM+LTR). Note that the alternative is simply the sum of the momentum past return (MOM) and the first definition of the long-term past return (LTR).[7] Table A.1 in the

[7] Following standard conventions, we exclude the prior month (-1) when calculating past returns. Although the one-month lagged return is significantly negatively correlated with returns (Jegadeesh (1990), Lehman (1990)), this dependence likely stems from market microstructure biases (Kaul and Nimalendran (1989)). We have confirmed that

Appendix provides detailed descriptions for all of our analysis variables.

4.1.2. Excess capacity

We construct our main excess capacity proxy from an SFA of a firm's installed capacity. The SFA methodology assumes that installed capacity can be either on the frontier or above it, but never below it. This asymmetry is captured by modelling optimal capacity as an affine function of several observable firm and industry characteristics plus the sum of two error terms. The first error term is identical to that used in ordinary least squares (OLS) models. The second is truncated from below at zero. It is zero for firms with optimal capacity and positive for firms with excess capacity.

Formally, we model optimal capacity, $K^*_{i,t}$, as:

$$K^*_{i,t} = \beta' \mathbf{D}_{i,t-1} + v_{i,t}, \tag{16}$$

where β is a vector of parameters, $\mathbf{D}_{i,t-1}$ is a vector of factors determining optimal capacity, and $v_{i,t}$ is an error term, with $v \sim N[0, \sigma^2_v]$. The explanatory variables are lagged by one year to allow for the fact that real firms require time to build new capacity.[8] To capture the difference between optimal and installed capacity, the SFA model adds the second error term to optimal capacity:

$$K_{i,t} = K^*_{i,t} + u_{i,t} = \beta' \mathbf{D}_{i,t-1} + v_{i,t} + u_{i,t}, \tag{17}$$

where $u \sim TN^+[\mu_{i,t-1}, \sigma^2_u]$, TN^+ indicates the normal distribution truncated from below at zero, and $\mu_{i,t-1}$ is the conditional mean of the second error term. We model the conditional mean as an affine

controlling for the one-month lagged return does not materially change our conclusions.

[8]In particular, consistent with Fama's (1990) finding that stock returns lead industrial production by approximately one year, we assume that the optimal *realizable* capacity implied by the explanatory variables is only reflected in installed capacity after one year.

function of factors that the Pindyck (1988) model predicts to be associated with excess capacity. In particular, we set $\mu_{i,t-1} = \gamma' \mathbf{E}_{i,t-1}$, where γ is a parameter vector, and $\mathbf{E}_{i,t-1}$ is a vector containing the explanatory variables. We estimate the parameters in Equation (17), which are β, γ, σ_v^2, and σ_u^2, using standard maximum likelihood techniques.

We use total assets to proxy for installed capacity. However, because total assets includes items such as goodwill and other intangible assets, we repeat the analysis using fixed assets or gross property, plant, and equipment (PP&E) as our capacity proxy. Our results are not sensitive to different capacity definitions. We divide capacity by sales to mitigate scale effects resulting in strong heteroscedasticity in the residual, and then take the natural log.[9] Scaling by sales has the further advantage that the endogenous variable becomes the inverse of the asset turnover ratio, which is often used by financial analysts to proxy for operating efficiency.

Equation (5) can be interpreted as an implicit function relating optimal capacity (K^*) to demand (θ), the elasticity of demand (γ), production costs (c_1 and c_2), installation costs (k), the risk-free rate of return (r), systematic risk (μ; through δ), and demand uncertainty (σ; through β_1 and β_2). In turn, demand can be estimated from the profit margin, production costs, and capacity. Assuming that our sample firms operate in a nearly perfectly competitive market (implying $\gamma = 0$), and ignoring cross-sectional constants (r) or unobservable variables (k), we approximate optimal capacity by using a firm's profit margin (PM), the industry profit margin (IPM), sales (SALE), the market beta (BETA), market size (SIZE), the book-to-market ratio (BM), and stock volatility (VOL). The exact definitions of these variables (and the ones introduced below) are in Table A.1. The first three variables should jointly be informative about product demand and production costs. Market beta, market size, and the book-to-market ratio are meant to capture systematic risk, although the book-to-market ratio could also proxy for the existence of not yet fully developed growth opportunities that become exercisable

[9]While certain extensions of the basic SFA model would allow us to directly model heteroscedasticity in the residual, these unfortunately do not allow us to make the truncated error term depend on exogenous variables.

only in the future. Finally, stock volatility serves as a proxy for demand volatility.

In the Pindyck (1988) model, a current demand below the historical maximum is necessary for excess capacity to arise. We thus model the conditional mean of the error term capturing excess capacity as an affine function of the difference between current sales and the historical maximum of sales, where we scale by the historical maximum and deflate sales by the consumer price index (DSALEMAX). To account for the fact that real firms are able to divest at some cost, we also include an interaction between DSALEMAX and the number of years since the historical maximum occurred (TDSALEMAX). Finally, we include a dummy equal to one if the firm reports a loss in the current fiscal year, but not in at least one of the previous four, and zero otherwise (LOSS).

We estimate the SFA models over recursive windows and separately for each of the Campbell (1996) industries, excluding the financial, real estate, and utilities industries. See Table A.1 for the industry definitions. We exclude financial and real estate firms because their accounting data are not comparable with those of non-financial firms. We exclude utilities because their investment decisions depend on the regulatory environment. We further exclude any observation for which a merger or acquisition took place between the dates on which the endogenous and exogenous variables are measured. The initial recursive window ranges from January 1972 through December 1979. We re-estimate the models annually through December 2010. Using the estimates obtained from the recursive window ending in month t, we estimate optimal capacity at t. The estimate of excess capacity (EXCAP) is the difference between installed capacity at time t and estimated optimal capacity. The estimate can be negative due to the fact that we allow for time-to-build in the estimations.

Table 2 shows the results from the SFA models estimated over the final (full sample) recursive window. The profit margin (PM) has a significantly positive effect in eight of the ten industries, consistent with the prediction that high profitability raises optimal capacity. Recalling that the endogenous variable is scaled by sales, the coefficients on sales (SALE), which are always greater than minus one, can be interpreted similarly. In contrast, the industry profit margin (IPM) coefficient is significantly positive in two industries, but significantly negative in seven. These differences in sign might be explained by whether growth opportunities are monopolistic. Unless they are, there is the danger that competitors "steal" growth opportunities, inducing more conservative investment behavior (Aguerrevere (2009)). Although the market beta (BETA) is sometimes significant, it has no economically meaningful effect. Market capitalization (SIZE) and the book-to-market ratio (BM) are always positively and strongly significantly correlated with optimal capacity, possibly because larger firms have a lower systematic risk (Berk (1995)) and growth firms possess more as yet un-exercisable growth options (Carlson et al. (2004)). Surprisingly, stock volatility (VOL) always commands a consistently positive coefficient. This contradicts the hypothesis that uncertainty induces firms to invest more conservatively (Pindyck (1988)). However, the positive coefficients are driven by a large negative correlation between SIZE and VOL. Dropping SIZE from the statistical model renders the stock volatility-optimal capacity relationship strongly negative.

In the majority of cases, the signs of the excess capacity coefficients are also as predicted. A greater deviation between current sales and their historical maximum (DSALEMAX) results in a significantly higher excess capacity in all industries. However, consistent with the notion that firms are able to slowly divest capacity, the interaction term between DSALEMAX and the number of years since the maximum occurred (TDSALEMAX) attracts a significantly negative coefficient in seven industries. The dummy variable for whether a firm reported a loss in the current fiscal year, but not in any of the prior four years (LOSS), produces mixed results. The coefficient is significantly positive in seven industries, but it is significantly negative in three industries.

To validate EXCAP, Figure 4 compares its median with an industry capacity under-utilization estimate calculated from Bureau of Economic Analysis (BEA) surveys over our sample period. To enhance comparability, we only use those firms operating in industries surveyed by the BEA in this figure. To calculate median capacity under-utilization, we assign the capacity under-utilization value of an industry to all firms operating in it and then take the cross-sectional median. In theory, an increase in excess capacity should not affect capacity under-utilization when excess capacity is low to begin with. However, when excess capacity is high, increases in excess capacity should translate one-to-one into increases in capacity under-utilization. Thus, we expect the two series to be positively correlated, and we further expect higher correlations during recessions. Our evidence strongly confirms these predictions. There is a strong positive correlation of 0.676 between the two series. Moreover, both series increase sharply during NBER-defined recessions (the grey areas), with the correlation rising to 0.767 in these periods.[10] Despite this, the survey estimate often leads the excess capacity proxy by around one to two months. The lower timeliness of the excess capacity proxy may be driven by our assumption that investors obtain accounting data two months after the fiscal quarter-end, implying that the SFA data could be out-of-date by as much as five months.

4.1.3. Control variables

Our multivariate tests control for effects of the market beta (BETA), market size (SIZE), the book-to-market ratio (BM), and share illiquidity (ILLIQ). We use Lewellen and Nagel's (2006) approach to obtain an estimate of the conditional market beta for each single stock. In particular, we perform the following stock-specific time-series regression over the prior twelve months of daily data:

$$r_{i,t} = \alpha_i + \beta_{i,1}^{mkt} r_{mkt,t} + \beta_{i,2}^{mkt} r_{mkt,t-1} + \beta_{i,3}^{mkt} (r_{mkt,t-2} + r_{mkt,t-3} + r_{mkt,t-4}) + \varepsilon_{i,t}, \tag{18}$$

where $r_{i,t}$ is the excess return of stock i at time t, $r_{mkt,t}$ is the market excess return, α_i, $\beta_{i,1}^{mkt}$, $\beta_{i,2}^{mkt}$, and $\beta_{i,3}^{mkt}$ are parameters, and $\varepsilon_{i,t}$ is the residual. The beta estimate at the end of the rolling window is then given by the sum of the slope coefficients. We add the lagged factors to alleviate biases associated

[10]The corresponding numbers for the time-series of the means are 0.590 and 0.717, respectively.

with non-synchronous trading (Dimson (1979)). In contrast to Lewellen and Nagel (2006), who estimate portfolio betas, we run the time-series regression over a longer prior period (twelve months instead of one) to decrease the standard errors of the firm-specific beta estimates. We use the Amihud (2002) measure to proxy for share illiquidity. All definitions are again given in Table A.1.

4.2. Data

Market and accounting data are from CRSP and COMPUSTAT, respectively. We only study common stock traded on the NYSE, the AMEX, or the NASDAQ. For comparability reasons, we exclude financials and utilities. On delisting, we replace a stock's return with its delisting return if the latter is available. If it is unavailable, but the delisting code suggests the delisting was performance-related (500; 520-584), we set the returns of NYSE and AMEX stocks to -30% and those of NASDAQ stocks to -55% (see Shumway (1997), Shumway and Warther (1999)). To increase timeliness, we use quarterly accounting data in the excess capacity estimations. Consistent with prior studies, we assume that quarterly accounting data become available with a two month lag, and annual accounting data with a three month lag. The corporate and government bond portfolio data (used in the time-series regressions) come from Datastream. Earnings growth forecasts (used in the descriptive statistics to validate EXCAP) are from I/B/E/S. We obtain the benchmark factors from Kenneth French's website, and the NAICS industry data from the website of the Federal Reserve.[11]

To mitigate the influence of outliers, we winsorize all variables at the 1st and 99th percentiles, estimated separately by month, except for the (future) stock return and the share illiquidity measure (ILLIQ). Consistent with Amihud (2002), the share illiquidity measure is winsorized at the 5th and 95th percentiles, estimated separately by month. Our sample period for all statistical tests, except the recursive SFA estimations, is January 1980 through December 2010.

[11]The URLs are <mba.tuck.dartmouth.edu/pages/faculty/ken.french/> and <federalreserve.gov/>.

4.3. Main findings

4.3.1. Descriptive statistics

In Table 3, we compare stocks with high and low EXCAP values. To achieve this goal, we sorts stocks into decile portfolios according to their EXCAP values and the EXCAP decile breakpoints in month $t-1$. We hold these portfolios over the entire month t and then re-sort them again. For each portfolio, we calculate the time-series mean of the cross-sectional median of each analysis variable, a long-term earnings growth forecast, and two investment indicators. The long-term earnings growth forecast is the I/B/E/S consensus long-term earnings growth forecast for month t. The two investment indicators are the growth rate in gross PP&E from the prior fiscal year to the current fiscal year (PPEG) and capital expenditures scaled by total assets (CPX).

Panel A shows that EXCAP is strongly negatively related to MOM, LTR, and MOM+LTR. Low excess capacity stocks tend to have experienced very positive returns over the recent past, while high excess capacity stocks tend to have experienced very negative ones. Confirming our intuition, excess capacity becomes more negatively related to past returns as we increase the length of the period over which past returns are calculated (MOM versus MOM+LTR). However, also in line with our intuition, the negative relationship becomes weaker if we drop the most recent year from the period over which we calculate past returns (LTR versus MOM+LTR). High excess capacity stocks tend to attract low market values (SIZE) and low long-term growth forecasts (CEG). However, both high and low excess capacity stocks tend to be value stocks (BM). Also, they both tend to have high market betas (BETA) and to suffer from a high share price illiquidity (ILLIQ).

In Panel B, we compare investments across high and low EXCAP stocks. Two years prior to portfolio formation, the PP&E growth rates and capital expenditures of the highest EXCAP stocks (7.7% and 4.2%, respectively) are similar to those of the lowest EXCAP stocks (8.1% and 5.3%, respectively). However, starting from then, the spreads in these numbers across high and low EXCAP stocks widen significantly. In particular, the PP&E growth rates of the highest EXCAP stocks decline first to 5.7% and then to 3.0%, while their capital expenditures decline first to 3.7% and then to 3.2%. In contrast, the lowest EXCAP stocks manage to slightly increase their PP&E growth rates and capital expenditures over the same periods. Given that EXCAP does not depend on these two investment indicators, the above evidence is consistent with the idea that EXCAP efficiently captures excess capacity—and thus provides construct validity.

4.3.2. Cross-sectional tests

In Table 4, we test Hypotheses H1 and H2. We thus calculate the mean returns of portfolios double-sorted on EXCAP and one of the past returns. The past return is MOM in Panel A, LTR in Panel B, and MOM+LTR in Panel C. To be consistent with the hypotheses, we use sequential sorts. More specifically, we first stocks into portfolios according to their EXCAP values. Within each EXCAP portfolio, we then sort stocks into portfolios according to the relevant past returns. As breakpoints, we use the quartiles of the past returns measured using data up to month $t-2$ and EXCAP measured in month $t-1$. We also create spread portfolios using only stocks in given EXCAP quartiles. The spread portfolios are long on the high past return portfolio and short on the low past return portfolio (H-L). The portfolios are equally-weighted and held over the entire month t. We report unadjusted (unadj) and CAPM- or Fama-French/Carhart (FFC) model-adjusted mean returns for the spread portfolios. The adjusted returns are the intercepts from the full sample time-series regressions of the spread portfolio return on the excess market return (CAPM adjustment) or on the excess market return, SMB, HML and MOM (in Panels B and C) or LTR (in Panel A; FFC adjustment).

Hypothesis H1 suggests that momentum profits decline with excess capacity. We thus anticipate that the momentum spread portfolio formed from low EXCAP stocks yields a higher (more positive) mean return than the momentum spread portfolio formed from high EXCAP stocks. Panel A strongly supports this prediction. Among stocks with an EXCAP value in the bottom quartile, the mean return spread between winners and losers is 8.13% per year (t.stat: 2.50). The spread portfolio return drops to 4.66% (t-stat: 1.53) among stocks with an EXCAP value in the second quartile, to 3.34% (t-stat: 0.96) among stocks with an EXCAP value in the third quartile, and to -1.94% (t-stat: -0.35) among stocks with an EXCAP value in the top quartile. Adjusting for the CAPM or FFC benchmark factors does not change the fact that momentum effects are significant within the low excess capacity quartiles and insignificant within the higher excess capacity quartiles.

Hypothesis H2 suggests that long-term reversal profits increase with excess capacity. We thus anticipate that the long-term past return spread portfolio formed from low EXCAP value stocks yields a higher (less negative) mean return than the long-term past return spread portfolio formed from high EXCAP value stocks. Panels B and C strongly support this prediction. For example, in Panel B, the mean return spread between winners and losers is -8.31% per year (t-stat: -2.38) among stocks in the bottom EXCAP value quartile. This spread portfolio return drops to -10.11% (t-stat: -2.96) among stocks in the second EXCAP value quartile, to -12.44% (t-stat: -3.24) among stocks in the third EXCAP value quartile, and to -16.79% (t-stat: -3.11) among stocks in the top EXCAP value quartile. Adjusting for the CAPM or FFC benchmark factors does again not change the fact that the long-term reversal effect is far more significant in the higher excess capacity quartiles.

Separately studying the mean returns of winner and loser stocks, we find that the mean returns of winners always strongly decline with EXCAP, while the mean returns of losers either stay flat (LTR) or slightly increase with EXCAP (MOM+LTR). Because winners should be located close to the left boundary of each region in Figure 3, the pattern produced by them is consistent with Pindyck's (1988) model. In contrast, losers should be located closer to the right boundary of each region in Figure 3. Judging whether the pattern produced by them is consistent with Pindyck's (1988) model is more difficult because the model-implied pattern depends strongly on how reversible investment are (recall Figure 2). The result that the mean returns of the MOM+LTR loser portfolios slightly increase with EXCAP suggests that investments cannot be highly reversible. Still, the positive association is not strong, and so investments are also unlikely to be completely irreversible.

In Table 5, we report the results of Fama and MacBeth (1973) regressions of the stock return on different sets of pricing factors. Estimates are in bold, while Newey and West (1987) t-statistics (with the lag parameter set to twelve) are in square parentheses. The pricing factors include the past returns (MOM, LTR, and MOM+LTR), the market beta (BETA), market size (SIZE), the book-to-market ratio (BM), and share illiquidity (ILLIQ). To test Hypotheses H1 and H2, we include interactions between past returns and a rank variable created from the excess capacity proxy (REXCAP). The rank variable is zero if excess capacity is in the first quartile, 0.333 if it is in the second quartile, 0.666 if it is in the third quartile, and 1 otherwise. We sometimes control for the separate effect of REXCAP. We again base past returns on data up to month $t-2$ and other factors on data up to month $t-1$. The above approach is equivalent to running one Fama and MacBeth (1973) regression per excess capacity quartile, allowing the effect of the past returns (and sometimes the constant) to linearly vary across regressions, but restricting the effects of the controls to be the same.

Using a standard set of controls excluding REXCAP, the multivariate tests yield a weak momentum effect, but a stronger long-term reversal effect (Panel A). In particular, model 1 suggests that the momentum effect is 0.446% per month (t-stat: 1.87), while model 3 suggests that the long-term reversal effect, calculated using LTR, is -0.370% per month (t-stat: -2.31). However, excess capacity strongly conditions these effects. For example, the slope coefficient on the interaction between MOM and REXCAP in model 2 is -0.643 (t-stat: -2.68), indicating that the momentum returns generated by the low EXCAP firms exceed those generated by the high EXCAP firms by an average of 64 basis points per month. The slope coefficient on the interaction between LTR and REXCAP in model 4 is -0.585 (t-stat: -3.70), indicating that the long-term reversal returns generated by the high

EXCAP stocks are more negative than those generated by the low EXCAP stocks by an average of 59 basis points per month. The above results are robust against: (i) jointly examining momentum and long-term reversal effects in models 5 and 10, (ii) studying the alternative instead of the conventional long-term past return in models 5 and 10 (the effects of the alternative proxy are the sum of the effects of the other two past returns; see Panel B), and (iii) adding REXCAP to the controls.

The controls create effects consistent with those reported by the prior literature. Although the market beta (BETA) has no power to explain stock returns, market size (SIZE) and the book-to-market ratio (BM) do, at least before controlling for LTR (Fama and French (1992)). The fact that LTR drives out the size and book-to-market effects is attributable to its high correlations with these variables (not reported). In line with Amihud (2002), we sometimes observe a weakly positive relationship between the share illiquidity proxy and stock returns. Interestingly, REXCAP is strongly negatively correlated with stock returns at a highly significant confidence level.

Overall, the multivariate tests also support the hypotheses that momentum effects become weaker with excess capacity, while long-term reversal effects become stronger with it.

4.3.3. Time-series tests

In Table 6, we test Hypotheses H3 and H4. To this end, we run time-series regressions of momentum or long-term reversal effects on aggregate excess capacity, aggregate capacity under-utilization, and other macroeconomic controls. The effects are the returns of spread portfolios long on the high past return quartile and short on the low past return quartile, where the past return is the momentum return (MOM; Panel A), the conventionally-used long-term past return (LTR; Panel B), or the alternative long-term past return (MOM+LTR; Panel C). We form the portfolios in the same way as in Table 4. Aggregate excess capacity is the simple cross-sectional mean of the excess capacity proxy (AEXCAP). Aggregate capacity under-utilization (ACPUUTL) is the cross-sectional mean of the industry-level survey capacity under-utilization estimate, weighted by the number of firms per industry. The controls include an indicator variable equal to one in NBER-defined recessions and zero otherwise (NBER), the return spread between 20-year and one-year government bonds (UTS), and the return spread between high-yield and AAA-rated corporate bonds (UPR).[12] The predictors are lagged by two months. Estimates are in bold, and t-statistics, calculated using the Newey and West (1987) formula (using a lag length parameter equal to twelve), are in square parentheses.

Panel A shows that AEXCAP strongly predicts momentum returns. Its coefficient is negative and significant at the 95% confidence level, and it explains approximately 4.83% of the variations in momentum returns when employed on its own. In contrast, ACPUUTL is only weakly significant when we also control for other macroeconomic effects, but not for AEXCAP. Employed on its own, it has an R-squared of only 1.75%. No other control shows any signs of conditioning momentum effects.[13] Panels B and C document that both AEXCAP and ACPUUTL predict long-term reversal effects with significant negative coefficients and R-squareds in the range of 2%-5%. However, AEXCAP drives out ACPUUTL when they are included together. The term spread (UTS) and the default risk spread (UPR) also forecast the conventionally-defined long-term reversal effect with significant negative coefficients, but this does not affect our conclusions about AEXCAP or ACPUUTL. Overall, these tests show that, when average excess capacity is high, momentum profits tend to be lower, while long-term reversal profits tend to be higher, supporting Hypotheses H3 and H4.

4.3.4. Graphical summary of main results

Figure 5 graphically illustrates our findings. The figure shows the cumulative (arithmetic) returns of momentum and long-term reversal spread portfolios formed from stocks in the highest and the

[12]Using yields instead of returns significantly decreases the predictive ability of the last two controls.

[13]Nyberg and Pövry (2013) show that the time-series profits of momentum strategies are significantly positively related to lagged aggregate asset growth. Given that asset growth relates negatively to excess capacity, their findings are consistent with ours.

lowest EXCAP quartiles over the sample period.[14] In Panel A, the spread portfolios are long the highest MOM quartiles and short the lowest ones. In Panels B and C, the spread portfolios are long the lowest LTR or MOM+LTR quartiles and short the highest ones. At the bottom of each panel, we also plot aggregate excess capacity (AEXCAP). The shaded vertical bars indicate NBER-defined recession periods, and the vertical lines highlight periods in which aggregate excess capacity was substantially above its time-series mean (around 0.46).

We can draw the following conclusions from the figure:

(i) The momentum strategy works well when AEXCAP is relatively low, while long-term reversal strategies work well when AEXCAP is high. For instance, over the 1980-2000 period, AEXCAP is mostly below its sample period mean. Over this period, the momentum strategy is the most profitable, and the long-term reversal strategies are the least profitable. Following 2000, AEXCAP often reaches levels significantly above its sample mean, for example, in the 2000-2004 and 2008-2009 periods. Especially over the latter two periods, the performance of the momentum strategy was often disastrous. For example, over the six months following the highest observed AEXCAP value (March 2009) the momentum strategy lost more than 20% of its total value. Over exactly the same periods, long-term reversal strategies gained most (usually more than 10%) of their value. The above conclusions are entirely consistent with our time-series regression results.

(ii) The momentum strategy applied to low EXCAP stocks beats the one applied to high EXCAP stocks. In particular, the low EXCAP-MOM strategy has a cumulative return of 2.52 over the sample period, while for the high EXCAP-MOM strategy the cumulative return is -0.60. The performance gap is especially wide when AEXCAP is high, likely because it is in these periods that it is especially important to ensure that momentum strategies do not feature large numbers of stocks with substantial

[14] Strictly speaking, it is impossible to compound the returns of spread portfolios because their initial investment is equal to zero (Lehman (1990)). Ignoring this issue and compounding returns, we obtain conclusions that are virtually identical to those reported.

EXCAP. Take, for example, the 2008-2009 period, during which AEXCAP reaches its highest levels. Over this period, the low EXCAP-MOM strategy loses around 0.52 in value, but the high EXCAP-MOM strategy loses even around 1.03. In contrast, high EXCAP long-term reversal strategies beat low EXCAP long-term reversal strategies. In particular, the high EXCAP-LTR strategy yields a cumulative return of 5.20, while the low EXCAP-LTR strategy yields a cumulative return of only 2.57. Again, the performance gap between the two strategies becomes most pronounced when there are a significant number of high EXCAP stocks in the economy (i.e., when AEXCAP is high). The above conclusions are entirely consistent with our cross-sectional regression results.

4.3.5. Robustness

The SFA approach is rarely used in finance, and it has, to the best of our knowledge, so far not been used to model optimal capacity. Thus, there may be valid concern that our conclusions are driven by the SFA model picking up some effect unrelated to excess capacity. To address this concern, we now repeat our tests using a simpler indirect proxy for excess capacity. To derive the simpler proxy, recall first that the Pindyck (1988) model predicts that firms expand their asset base as soon as current demand (θ) surpasses the optimal investment threshold (θ^*). Thus, the probability of a firm investing into new capacity in the future depends on the current level of demand relative to the optimal investment threshold. If current demand is at or very close to the threshold, the probability of investing is approximately equal to 50% because demand follows Geometric Brownian motion. If current demand is further below the threshold, the probability of investing into new capacity in the future is lower. Second, note that the Pindyck (1988) model produces a perfectly positive correlation between the current demand-optimal investment threshold difference and excess capacity. Hence, the model also produces the (extremely intuitive) prediction that the probability of a firm investing into new capacity over some future period decreases with excess capacity.

We create a proxy for the probability of a firm investing into new capacity by running LOGIT model regressions. The endogenous variable in the LOGIT model is a dummy variable equal to one if a firm's total assets increase from fiscal years $t-1$ to t, and zero else. The exogenous variables are the same variables as those used to model optimal capacity plus log total asset growth measured over fiscal years $t-2$ to $t-1$. Identical to the SFA models, the LOGIT models are estimated recursively and separately by Campbell (1996) industry. We use the model estimates in combination with the most recent exogenous variable values from the recursive windows to calculate firm i's probability of investing into new capacity over the next fiscal year, measured at time t (PINV).

The mean cross-sectional correlation between PINV and EXCAP is 0.33. Using PINV instead of EXCAP in the portfolio sorts, the Fama-MacBeth (1973) regressions, and the time-series regressions, we obtain empirical results qualitatively identical to those reported in Tables 3-7. To conserve space, we do not report these results, but they are available from the authors upon request. Overall, the robustness tests offer further support for the idea that excess capacity is a major determinant of both momentum and long-term reversal effects in U.S. stock returns.

5 Conclusion

In this paper, we show that a real options-based investment model, in which reversibility of investments is costly, can explain momentum and long-term reversal effects through a channel linking past returns to excess capacity – the difference between optimal and installed capacity. Excess capacity and capacity utilization affect the values and elasticities of production and growth options, and hence expected returns. We show analytically that the relation between expected return and excess capacity is non-linear, being initially decreasing and subsequently increasing. We then predict that momentum and long-term winners plot on the left side of the U-shaped relationship, momentum losers in the middle (at the bottom of the U-shape), and long-term losers on the right side, thereby jointly explaining momentum and long-term reversal effects in asset returns.

In our empirical work, we develop a fundamentals-based proxy for excess capacity. We show that this proxy strongly conditions the returns to both momentum and long-term reversal strategies, confirming our theoretical predictions. In cross-sectional analysis, we show that momentum effects are only significant for the group of stocks with lowest excess capacity; and that long-term reversal effects are only significant for the group of stocks with the highest excess capacity. Also consistent with our theory, time series tests show that momentum returns depend negatively on aggregate excess capacity, while long-term reversal returns depend positively on aggregate excess capacity.

Our results are consistent with the momentum and long-term reversal effects in stock returns being grounded in the fundamental economics of firms. Our evidence indicates that returns to momentum and long-term reversal strategies capture risk premia associated with firms' production and growth options. Future research might examine whether the factors underling other unexplained market anomalies are effectively capturing additional information on the investment and operating conditions that drive these risk premia.

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Appendix:

A The definitions of β_1, β_2, b_1, b_2, and a

The definitions of $\beta_1, \beta_2, b_1, b_2$, and a are as follows:

$$\begin{aligned}
\beta_1 &= -\frac{(r-\delta-\sigma^2/2)}{\sigma^2}+\frac{1}{\sigma^2}\left[(r-\delta-\sigma^2/2)^2+2r\sigma^2\right]^{(1/2)} > 1,\\
\beta_2 &= -\frac{(r-\delta-\sigma^2/2)}{\sigma^2}-\frac{1}{\sigma^2}\left[(r-\delta-\sigma^2/2)^2+2r\sigma^2\right]^{(1/2)} < 0,\\
b_1 &= \frac{r-\beta_2(r-\delta)}{r\delta(\beta_1-\beta_2)}[(2\gamma+c_2)K+c_1]^{1-\beta_1} > 0,\\
b_2 &= \frac{r-\beta_1(r-\delta)}{r\delta(\beta_1-\beta_2)}[(2\gamma+c_2)K+c_1]^{1-\beta_2} > 0,\\
a &= \frac{\beta_2 b_2}{\beta_1}(\theta^*)^{(\beta_2-\beta_1)}+\frac{1}{\delta\beta_1}(\theta^*)^{(1-\beta_1)} > 0.
\end{aligned}$$

The inequalities are from Pindyck (1988).

B Proof of Lemma 1

We aim to show that the value of the option to install the production unit producing the vth output unit, $\Delta F(v,\theta)$, is bounded from above by the value of the same production unit, $\Delta V(v,\theta)$.

This must necessarily be the case if the following three conditions hold:

1. $\Delta V(v,\theta)$ and $\Delta F(v,\theta)$ converge to the same limit (zero) as θ approaches zero from above.

2. Over the region $\theta = \{0, \theta^*\}$, $\Delta V(v,\theta)$ increases with θ at a more positive rate than $\Delta F(v,\theta)$.

3. Over the region $\theta = \{\theta^*, +\infty\}$, $\Delta V(v,\theta)$ and $\Delta F(v,\theta)$ increase with θ at the same rate.

To see that the first condition holds, we note that:

$$\lim_{\theta \to 0^+} \Delta V(v,\theta) = \lim_{\theta \to 0^+} b_1 \theta^{\beta_1} = 0,$$

and also:

$$\lim_{\theta \to 0^+} \Delta F(v,\theta) = \lim_{\theta \to 0^+} a \theta^{\beta_1} = 0,$$

where the equalities follow from $\beta_1 > 0$ (see Appendix A).

To see that the second condition holds, we evaluate the partial derivatives of the option values with respect to θ separately over the $\theta = \{0, (2\gamma + c_2)K + c_1\}$ and $\theta = \{(2\gamma + c_2)K + c_1, \theta^*\}$ regions. In the latter region, the condition that the partial derivative of the production option must exceed that of the growth option becomes:

$$\beta_2 b_2 \theta^{\beta_2 - 1} + \frac{1}{\delta} > (\beta_2 b_2 (\theta^*)^{\beta_2 - \beta_1} + \frac{1}{\delta}(\theta^*)^{1-\beta_1})\theta^{\beta_1 - 1}.$$

Re-arranging:

$$\beta_2 b_2 \theta^{\beta_2 - \beta_1} + \frac{\theta^{1-\beta_1}}{\delta} > \beta_2 b_2 (\theta^*)^{\beta_2 - \beta_1} + \frac{(\theta^*)^{1-\beta_1}}{\delta},$$

which holds because $\beta_2 - \beta_1 < 0$, $1 - \beta_1 < 0$ and $\theta < \theta^*$.

In the former region, the second condition becomes:

$$\beta_1 b_1 \theta^{\beta_1 - 1} > \beta_1 a \theta^{\beta_1 - 1},$$

or:

$$b_1 > a.$$

When $\theta = (2\gamma + c_2)K + c_1$ (i.e., demand is at the production threshold), smooth-pasting implies that the partial derivatives of the two component solutions of the option to produce ($b_1\theta^{\beta_1}$; and $b_2\theta^{\beta_2} + \theta/\delta - [(2\gamma + c_2)K + c_1]/r$), both with respect to θ, are identical. More specifically, it must hold that:

$$\beta_2 b_2 (\theta^P)^{\beta_2 - 1} + \frac{1}{\delta} = \beta_1 b_1 (\theta^P)^{\beta_1 - 1},$$

where, for notional convenience, we use the definition $\theta^P \equiv (2\gamma + c_2)K + c_1$ in the equality above. We know from evaluating the $\theta = \{(2\gamma + c_2)K + c_1, \theta^*\}$ region that $\beta_2 b_2 (\theta^P)^{\beta_2 - 1} + \frac{1}{\delta} > \beta_1 a (\theta^P)^{\beta_1 - 1}$. In turn, this implies that $\beta_1 b_1 (\theta^P)^{\beta_1 - 1} > \beta_1 a (\theta^P)^{\beta_1 - 1}$. One implication of the last inequality is that $b_1 > a$.

To see that the third condition holds, note that, if $\theta > \theta^*$, the value of the growth option is equal to that of the production option minus the installation costs. The partial derivatives of the production option and the growth option, both with respect to θ, must thus be exactly identical.

C Proof of Lemma 2

We aim to show that the elasticity of the non-idle production option is bounded from above by β_1, which is the elasticity of an unused production option or an unexercised growth option. More specifically:

$$\beta_1 \geq \frac{b_2\beta_2\theta^{\beta_2}+\theta/\delta}{b_2\theta^{\beta_2}+\theta/\delta-[(2\gamma+c_2)K+c_1]/r}$$

over the region $\theta = \{(2\gamma+c_2)K+c_1, \infty\}$.

To achieve this, multiply the above inequality by $\Delta V(v,\theta) = b_2\theta^{\beta_2}+\theta/\delta-[(2\gamma+c_2)K+c_1]/r > 0$, which is the value of the non-idle production option, and then re-arrange as follows:

$$(\beta_1-\beta_2)b_2\theta^{\beta_2}+(\beta_1-1)\theta/\delta-\beta_1[(2\gamma+c_2)K+c_1]/r) \geq 0.$$

Now substitute the solution of b_2 from Appendix A into the above inequality:

$$\frac{r-\beta_1(r-\delta)}{r\delta}[(2\gamma+c_2)K+c_1]^{1-\beta_2}\theta^{\beta_2}+(\beta_1-1)\theta/\delta-\beta_1[(2\gamma+c_2)K+c_1]/r) \geq 0.$$

Multiply by $r>0$ and $[(2\gamma+c_2)K+c_1]^{(\beta_2-1)}\theta^{(-\beta_2)}>0$ and re-arrange again:

$$\frac{r-\beta_1(r-\delta)}{\delta}+\frac{r(\beta_1-1)}{\delta}\left(\frac{\theta}{(2\gamma+c_2)K+c_1}\right)^{(1-\beta_2)}-\beta_1\left(\frac{\theta}{(2\gamma+c_2)K+c_1}\right)^{(-\beta_2)} \geq 0. \quad (19)$$

We next show that (i) the left-hand side of Inequality (19) is zero at $\theta = \theta^P$, and (ii) it increases above zero as θ rises above θ^P. To observe that condition (i) holds, we can plug the definition of θ^P into the left-hand side of the inequality, and note the following accounting identity:

$$\beta_1 = \frac{r-\beta_1(r-\delta)}{\delta}+\frac{r(\beta_1-1)}{\delta}.$$

To prove condition (ii), note that the partial derivative of the left-hand side of Inequality (19) with respect to θ is:

$$\frac{1}{(2\gamma+c_2)K+c_1}\left[\frac{r(1-\beta_2)(\beta_1-1)}{\delta}\left(\frac{\theta}{(2\gamma+c_2)K+c_1}\right)^{-\beta_2}+\beta_1\beta_2\left(\frac{\theta}{(2\gamma+c_2)K+c_1}\right)^{-\beta_2-1}\right],$$

and that the sign of this partial derivative is positive if and only if:

$$\frac{r(1-\beta_2)(\beta_1-1)}{\delta}+\beta_1\beta_2\left(\frac{\theta}{(2\gamma+c_2)K+c_1}\right)^{-1}>0, \tag{20}$$

where $\frac{r(1-\beta_2)(\beta_1-1)}{\delta}>0$ and $\beta_1\beta_2\left(\frac{\theta}{(2\gamma+c_2)K+c_1}\right)^{-1}<0$ (because $\beta_2<0$).

Evaluating the partial derivative at $\theta=\theta^P$, we obtain:

$$\frac{r}{\delta}(\beta_1+\beta_2-\beta_1\beta_2-1)+\beta_1\beta_2.$$

Using the definitions of β_1 and β_2 in Appendix A, we can show that $\beta_1+\beta_2=-\frac{2(r-\delta-\sigma^2/2)}{\sigma^2}$ and $\beta_1\beta_2=-\frac{2r}{\sigma^2}$. Plugging these expressions for $\beta_1+\beta_2$ and $\beta_1\beta_2$ into the partial derivative evaluated at $\theta=\theta^P$, we find:

$$\frac{r}{\delta}\left(-\frac{2(r-\delta-\sigma^2/2)}{\sigma^2}+\frac{2r}{\sigma^2}-1\right)+\frac{2r}{\sigma^2}=\frac{r}{\delta}\left(-\frac{2r}{\sigma^2}+\frac{2\delta}{\sigma^2}+1+\frac{2r}{\sigma^2}-1\right)+\frac{2r}{\sigma^2}=0,$$

which in turn implies that the partial derivative is zero when θ is at θ^P. However, raising θ above θ^P, only the negative summand in Inequality (20) (the second one) is affected, and it changes from $\beta_1\beta_2$ to $\beta_1\beta_2((2\gamma+c_2)K+c_1)/\theta$. Given that $\theta>\theta^P\equiv(2\gamma+c_2)K+c_1$, $((2\gamma+c_2)K+c_1)/\theta<1$, which implies that the negative summand becomes smaller in magnitude and that Inequality (20) is fulfilled if $\theta>\theta^P$.

D The Pindyck (1988) model with reversible investment

This Appendix derives the values of the options to produce and to modify capacity in an augmented Pindyck (1988) model allowing firms to sell off installed capacity at a unit price of d. Other properties of Pindyck's (1988) model do not change.[15] The ability to sell capacity does not change the ordinary differential equations that the values of the production and growth options need to fulfill (see Equations (A2) and (A4) in Pindyck's (1988) Appendix). However, it does change the boundary conditions, which are now given by:

$$
\begin{aligned}
\lim_{\theta\to\infty} \Delta V(K,\theta) &= \theta/\delta - [(2\gamma + c_2)K + c_1]/r, & (21)\\
\Delta V(K,\theta^P,\text{operating}) &= \Delta V(K,\theta^P,\text{idle}), & (22)\\
\Delta V_\theta(K,\theta^P,\text{operating}) &= \Delta V_\theta(K,\theta^P,\text{idle}), & (23)\\
\Delta V(K,\theta^D) &= \Delta F(K,\theta^D) + d, & (24)\\
\Delta V_\theta(K,\theta^D) &= \Delta F_\theta(K,\theta^D), & (25)
\end{aligned}
$$

where $\theta^P \equiv (2\gamma + c_2)K + c_1$ is the optimal production threshold, and θ^D is the optimal divestment threshold, a new free parameter. The augmented model shares the first three boundary conditions with Pindyck's (1988) original model. The last two boundary conditions are new. The first new boundary condition specifies that the value of the production option must be equal to the value of the growth option plus the unit capacity selling price at the optimal divestment threshold. The second new boundary condition specifies that the value of the production option "smooth-pastes" into the value of the growth option at the optimal divestment threshold.

[15] To rule out a money machine, we require $k > d$.

The general solutions for the production option are:

$$\begin{aligned}\Delta V(K,\theta,\text{operating}) &= \alpha_{N1}\theta^{\beta_1}+\alpha_1\theta^{\beta_2}+\theta/\delta-[(2\gamma+c_2)K+c_1]/r,\\ \Delta V(K,\theta,\text{idle}) &= \alpha_2\theta^{\beta_1}+\alpha_3\theta^{\beta_2},\end{aligned}$$

where β_1 and β_2 are as in Appendix A, and α_1, α_2, α_3 and α_{N1} are free parameters. Using boundary condition (21), we find $\alpha_{N1}=0$. Substituting the general solutions into boundary conditions (22) and (23), we can further show that $\alpha_2=b_1$ and $\alpha_1-\alpha_3=b_2$, where b_1 and b_2 are given in Appendix A. Therefore, the value of the option to start production, $\alpha_2\theta^{\beta_1}$ (or $b_1\theta^{\beta_1}$ in the original model), does not depend on investment reversibility. However, because $\alpha_1>b_2$, which follows from $\alpha_3>0$ (the option to divest has a positive value), the value of the option to stop production, $\alpha_1\theta^{\beta_2}$ (or $b_2\theta^{\beta_2}$ in the original model), increases with investment reversibility.

The boundary conditions of the growth option, however, do not change:

$$\begin{aligned}\Delta F(K,0) &= 0, &(26)\\ \Delta F(K,\theta^*) &= \Delta V(K,\theta^*)-k, &(27)\\ \Delta F_\theta(K,\theta^*) &= \Delta V_\theta(K,\theta^*), &(28)\end{aligned}$$

where θ^* is again the optimal investment threshold. The general solution of the growth option is:

$$\Delta F(K,\theta) = \alpha_4\theta^{\beta_1}+\alpha_{N2}\theta^{\beta_2},$$

where α_4 and α_{N2} are free parameters. Using boundary condition (26), we find that $\alpha_{N2}=0$.

We are thus left with four boundary conditions, specifically (24), (25), (27) and (28), in four unknowns, α_1, α_4, θ^D and θ^*. Plugging the general solutions into these, we obtain the following system of equations:

$$\begin{aligned}
&\frac{(\alpha_1 - b_2)(\beta_1 - \beta_2)}{\beta_1}(\theta^D)^{\beta_2} - d = 0, \\
&\frac{(\alpha_4 - b_1)(\beta_1 - \beta_2)}{\beta_2}(\theta^D)^{\beta_1} - d = 0, \\
&\frac{\alpha_1(\beta_1 - \beta_2)}{\beta_1}(\theta^*)^{\beta_2} + \frac{(\beta_1 - 1)}{\delta\beta_1}(\theta^*) - \frac{(2\gamma + c_2)K + c_1}{r} - k = 0, \\
&\frac{\alpha_4(\beta_2 - \beta_1)}{\beta_2}(\theta^*)^{\beta_1} + \frac{(\beta_2 - 1)}{\delta\beta_2}(\theta^*) - \frac{(2\gamma + c_2)K + c_1}{r} - k = 0.
\end{aligned} \tag{29}$$

Interestingly, Equation (29) is identical to Equation (5) in Pindyck's (1988) original model, the implicit function that specifies the investment threshold, except that b_2 has been replaced with α_1. Given that $\alpha_1 < b_2$, the optimal investment threshold is different from that found in Pindyck (1988), although it is unclear whether it will be higher or lower. The above system of equations must be solved numerically for α_1, α_4, θ^D, and θ^*.

Table A.1: Variable and Industry Definitions[a]

MNEMONIC	Name	Description
Past Returns		
MOM	Short-term past return	Log gross return compounded over months -12 to -2
LTR	Long-term past return (Definition 1)	Log gross return compounded over months -36 to -13
MOM+LTR	Long-term past return (Definition 2)	Log gross return compounded over months -36 to -2
INDMOM/INDLTR	Industry short-term/long-term past return	Mean of MOM/LTR per Campbell (1996) industry
FIRMMOM/FIRMLTR	Firm short-term/long term past return	MOM minus INDMOM/LTR minus INDLTR
Excess Capacity-Capacity Under-utilization Measures		
EXCAP	Excess capacity	Total assets-to-sales minus total assets-to-sales estimated by SFM
REXCAP	Rank variable on excess capacity	Rank variable based on the quartiles of EXCAP estimated per month
CPUUTL	Survey capacity under-utilization	Industry-specific capacity under-utilization measured using surveys
Optimal Capacity-to-Sales Determinants		
PM	Profit margin	Sales-to-costs of goods sold
IPM	Industry profit margin	Median of sales-to-costs of goods sold per Campbell (1996) industry
SALE	Net Sales	Log(Sales)
BETA	Market beta	Market beta estimated using the Lewellen and Nagel (2006) method
SIZE	Market capitalization	Log(Share price $\times$ Number of common shares outstanding)
BM	Book-to-market ratio	Log(Book value-to-market value of a share)
VOL	Stock volatility	Stock volatility estimated using daily data over the prior twelve months
Excess Capacity-to-Sales Determinants		
DSALEMAX	Deviation from maximum sales	Current sales minus maximum sales over a firm's entire history
TDSALEMAX	Time since deviation from maximum sales	Number of years since the maximum value of sales occurred
LOSS	Loss dummy	Equal to one if a firm reports a loss in the most recent fiscal year, but not in at least one of the former four years, and zero otherwise
Controls/Other Variables		
BETA	Market beta	Market beta estimated using the Lewellen and Nagel (2006) method
SIZE	Market capitalization	Log(Share price $\times$ Number of common shares outstanding)
BM	Book-to-market ratio	Log(Book value-to-market value of a share)
ILLIQ	Stock illiquidity	Amihud (2002) illiquidity measure, computed as the mean of the ratio of the absolute return to trading volume over the prior twelve months of daily data
PPEG	PP&E growth	Gross %-change in gross PP&E
CPX	Capital expenditures	Capital expenditures-to-total assets
CEG	Consensus earnings growth forecast	IBES consensus long-term earnings growth forecast (in %)
Campbell (1996) Industry Definitions		
PTRL	Petroleum	SIC 13, 29
DURS	Consumer durables	SIC 25, 30, 36-37, 50, 55, 57
BASIC	Basic goods	SIC 10, 12, 14, 24, 26, 28, 33
FOOD	Food/tobacco	SIC 1, 20, 21, 54
CNSTR	Construction	SIC 15-17, 32, 52
CPTL	Capital goods	SIC 34-35, 38
TRSP	Transport	SIC 40-42, 44, 45, 47
TXTL	Textiles/trade	SIC 22-23, 31, 51, 53, 56, 59
SRVS	Services	SIC 72-73, 75, 80, 82, 89
LSR	Leisure	SIC 27, 58, 70, 78-79

[a] This table describes the variables used in the cross-sectional estimations. The table also shows the SIC codes used to construct the Campbell (1996) industries, excluding the finance/real estate and utilities industries.

Table 1: Stylized Example[a]

	ASSET 1	ASSET 2	ASSET 3	TOTAL
Firm A: No Excess Capacity				
Type of Asset	Asset-in-Place 1	Growth Option 1	Growth Option 2	
Used or Idle	used	N/A	N/A	
Elasticity	1.05	6.00	6.00	
Market Value	8.00	4.00	2.00	
Market Weight	0.57	0.29	0.14	
Expected Excess Return				0.25
Firm B: Mild Excess Capacity				
Type of Asset	Asset-in-Place 1	Asset-in-Place 2	Growth Option 2	
Used or Idle	used	used	N/A	
Elasticity	1.05	2.50	6.00	
Market Value	8.00	5.00	2.00	
Market Weight	0.53	0.33	0.13	
Expected Excess Return				0.17
Firm C: Significant Excess Capacity				
Type of Asset	Asset-in-Place 1	Asset-in-Place 2	Asset-in-Place 3	
Used or Idle	used	used	idle	
Elasticity	1.05	2.50	6.00	
Market Value	8.00	5.00	3.00	
Market Weight	0.50	0.31	0.19	
Expected Excess Return				0.20

[a] This table provides a stylized example illustrating the intuition behind the U-shaped excess capacity-expected return relationship generated by the Pindyck (1988) model. The firms in the example own three assets, Assets 1, 2 and 3. Each asset is either an asset-in-place or a growth option that when exercised leads to the installation of an asset-in-place at some fixed cost. If assets-in-place, the three assets can be used to produce the first, second, and third units of output, with production costs increasing according to a convex cost function. However, the firm can also decide to costlessly shut down a unit of productive capacity (Used or Idle). The table gives the elasticity, the market value, and the market weight (the fraction of a firm's total market value captured by the asset) of each asset. While the elasticities and market values are assumed, they are consistent with the Pindyck (1988) model insofar as: (i) the elasticities of the assets-in-place increase over the output units; (ii) the elasticities of the growth options are constant and higher (equal) to those of used (idle) assets-in-place; (iii) the assets-in-place are worth more than the growth options, and the values of both options decrease over the output units. Because the expected excess return of the mimicking portfolio on demand is 8%, the expected excess return of a firm is 0.08 multiplied by a market value-weighted average over the elasticities of a firm's assets.

Table 2: Stochastic Frontier Analysis[a]

	PTRL	DURS	BASIC	FOOD	CNSTR	CPTL	TRSP	TXTL	SRVS	LSR
Panel A: Optimal Capacity-to-Sales										
PM	**0.049**	**0.004**	**0.009**	**-0.010**	**0.041**	**0.008**	**0.118**	0.006	**0.014**	**0.038**
IPM	**0.767**	**-0.016**	**-0.031**	**0.041**	**-0.085**	**-0.009**	**-0.145**	-0.006	**-0.115**	**-0.080**
SALE	**-0.509**	**-0.326**	**-0.415**	**-0.524**	**-0.395**	**-0.281**	**-0.443**	**-0.363**	**-0.434**	**-0.373**
BETA	**0.041**	-0.001	**0.007**	0.001	0.005	0.002	**0.021**	**-0.009**	**0.010**	0.002
SIZE	**0.459**	**0.348**	**0.473**	**0.571**	**0.409**	**0.310**	**0.535**	**0.351**	**0.462**	**0.397**
BM	**0.234**	**0.201**	**0.303**	**0.419**	**0.385**	**0.187**	**0.520**	**0.304**	**0.337**	**0.294**
VOL	**2.119**	**0.992**	**3.197**	**2.296**	**1.828**	**0.943**	**2.797**	**0.755**	**1.272**	**1.787**
CONS	**-2.435**	**-1.893**	**-3.015**	**-3.755**	**-2.288**	**-1.553**	**-3.363**	**-1.885**	**-2.765**	**-2.250**
Panel B: Excess Capacity-to-Sales										
DSALEMAX	**231.810**	**396.189**	**645.311**	**456.076**	**434.017**	**384.502**	**285.125**	**391.354**	**417.998**	**448.029**
TDSALEMAX	**-157.230**	**-73.438**	**-54.648**	21.537	-45.920	**-43.437**	-44.965	**-104.374**	**-107.423**	**-254.547**
LOSS	**15.170**	**16.548**	**-42.053**	**37.882**	**52.150**	**-11.804**	**126.517**	**28.979**	**-42.392**	**39.518**
CONS	**-324.891**	**-430.876**	**-572.382**	**-502.293**	**-542.367**	**-378.318**	**-483.966**	**-367.220**	**-551.294**	**-453.431**
Panel C: Residual Volatilities										
SIGMA U	**10.787**	**11.634**	**16.471**	**13.492**	**14.511**	**10.488**	**12.953**	**9.869**	**15.869**	**13.769**
SIGMA V	**0.475**	**0.275**	**0.327**	**0.302**	**0.292**	**0.244**	**0.387**	**0.281**	**0.343**	**0.295**
RATIO	**22.728**	**42.274**	**50.338**	**44.724**	**49.770**	**43.040**	**33.471**	**35.109**	**46.230**	**46.725**
Panel D: Diagnostics										
LL	-37,030	-90,170	-89,300	-19,560	-15,810	-73,690	-15,230	-32,880	-78,370	-33,000
Obs	39,964	156,856	96,041	28,965	22,102	153,272	19,692	66,374	93,357	45,335

[a] This table shows the results of stochastic frontier analysis (SFA) models estimated over the January 1972-December 2010 period. The endogenous variable in the SFA models is the log of the ratio of total assets-to-sales. The variables used to explain optimal capacity are given in Panel A, those used to explain excess capacity are in Panel B. Detailed descriptions of these variables are in Table A.1. The endogenous variable is lead by twelve months relative to the exogenous variables. The estimations exclude an observation if a merger or acquisition occurs between the date when the endogenous variable is measured (t) and the date when the exogenous variables are measured ($t-12$). The estimations are run separately on firms from the Campbell (1996) industries, excluding the financials/real estate and utilities industries. 'CONS' shows the estimated intercepts. Panel C shows the volatility of the OLS error term (SIGMA U), the volatility of the truncated normal error term (SIGMA V), and the ratio of the two (RATIO). Panel D gives the log-likelihood (LL) and the number of observations (Obs). Bold estimates indicate statistical significance at the 95% confidence level.

Table 3: Descriptive Statistics[a]

Panel A: Analysis Variables	MOM	LTR	MOM+LTR	EXCAP	BETA	SIZE	BM	ILLIQ	CEG
Decile 1	0.281	0.196	0.496	-0.263	0.999	0.194	0.540	3.133	0.171
Decile 2	0.172	0.197	0.378	-0.040	0.951	0.184	0.569	2.794	0.158
Decile 3-4	0.103	0.159	0.268	0.148	0.944	0.183	0.604	2.406	0.151
Decile 5-6	0.031	0.113	0.147	0.346	0.954	0.197	0.624	2.121	0.144
Decile 7-8	-0.048	0.059	0.010	0.575	0.971	0.191	0.638	1.930	0.143
Decile 9	-0.127	0.008	-0.126	0.867	0.997	0.154	0.627	2.094	0.147
Decile 10	-0.195	-0.052	-0.256	1.412	1.008	0.085	0.530	2.211	0.153

	PPEG			CPX			
Panel B: Investment Behavior	$-12,0$	$-24,-12$	$-36,-24$	t	$t-12$	$t-24$	$t-36$
Decile 1	1.105	1.085	1.081	0.055	0.053	0.053	0.053
Decile 2	1.084	1.076	1.074	0.054	0.054	0.053	0.054
Decile 3-4	1.066	1.066	1.067	0.051	0.051	0.053	0.054
Decile 5-6	1.054	1.061	1.064	0.048	0.050	0.051	0.053
Decile 7-8	1.043	1.059	1.069	0.044	0.048	0.051	0.052
Decile 9	1.036	1.059	1.074	0.039	0.044	0.048	0.052
Decile 10	1.030	1.057	1.077	0.032	0.037	0.042	0.045

[a] This table gives descriptive statistics for excess capacity-sorted portfolios. Panel A focuses on our main analysis variables plus long-term earnings growth, while Panel B focuses on two investment variables. A detailed description of the analysis variables is in Table A.1. To simplify interpretation, we take the exponential of log market capitalization (SIZE) and the log book-to-market ratio (BM; EXP(SIZE) and EXP(BM), respectively), and we report market capitalization in billions of dollars. We use accounting values from the last fiscal quarter-end that is at least two months in the past, except when we are calculating the gross percentage change in PP&E (PPEG) and capital expenditures-to-total assets (CPX), which are based on contemporaneous (non-lagged) accounting values. The excess capacity portfolios are formed using EXCAP values and the EXCAP decile breakpoints in month $t-1$, and they are held over month t. The entries in the table are calculated as the time-series mean of the cross-sectional median of an analysis variable. The sample period is January 1980-December 2010.

Table 4: Double-Sorted Portfolios[a]

EXCAP		Past Return Quartiles: 1 (low)	2	3	4 (high)	High - Low Past Return (H-L): unadj	CAPM	FFC
Panel A: MOM Past Return								
1 (low)	return	**15.71**	**17.32**	**20.52**	**23.84**	**8.13**	**6.77**	**9.64**
	t-statistic	[3.75]	[5.71]	[5.68]	[4.82]	[2.50]	[2.31]	[3.48]
	excap	-0.09	-0.10	-0.12	-0.19			
2	return	**16.88**	**15.79**	**17.21**	**21.55**	**4.66**	**4.83**	**6.61**
	t-statistic	[3.84]	[4.51]	[5.29]	[4.97]	[1.53]	[1.84]	[2.45]
	excap	0.23	0.22	0.22	0.21			
3	return	**15.79**	**13.89**	**15.18**	**19.13**	**3.34**	**4.55**	**5.96**
	t-statistic	[3.05]	[3.68]	[4.50]	[5.25]	[0.96]	[1.47]	[2.05]
	excap	0.50	0.49	0.48	0.48			
4 (high)	return	**17.39**	**11.55**	**11.58**	**15.45**	**-1.94**	**0.31**	**2.12**
	t-statistic	[2.41]	[2.43]	[2.84]	[3.77]	[-0.35]	[0.06]	[0.46]
	excap	1.26	1.13	1.09	1.14			
Panel B: LTR Past Return								
1 (low)	return	**23.64**	**20.32**	**18.13**	**15.33**	**-8.31**	**-8.77**	**-6.40**
	t-statistic	[4.52]	[5.75]	[5.29]	[4.08]	[-2.38]	[-2.57]	[-1.92]
	excap	-0.14	-0.12	-0.12	-0.14			
2	return	**23.34**	**18.13**	**16.76**	**13.22**	**-10.11**	**-10.48**	**-8.30**
	t-statistic	[4.52]	[5.15]	[5.64]	[3.48]	[-2.96]	[-3.24]	[-2.66]
	excap	0.22	0.22	0.22	0.22			
3	return	**23.23**	**14.89**	**15.11**	**10.80**	**-12.44**	**-12.46**	**-10.12**
	t-statistic	[4.19]	[4.10]	[4.76]	[2.95]	[-3.24]	[-3.35]	[-2.62]
	excap	0.49	0.48	0.48	0.48			
4 (high)	return	**23.44**	**14.60**	**11.32**	**6.65**	**-16.79**	**-17.11**	**-13.50**
	t-statistic	[3.27]	[3.08]	[2.88]	[1.55]	[-3.11]	[-3.27]	[-2.18]
	excap	1.25	1.12	1.10	1.15			
Panel C: MOM+LTR Past Return								
1 (low)	return	**21.09**	**18.89**	**18.70**	**18.72**	**-2.37**	**-3.64**	**-4.42**
	t-statistic	[4.21]	[5.50]	[5.71]	[4.33]	[-0.65]	[-1.06]	[-1.37]
	excap	-0.11	-0.11	-0.12	-0.17			
2	return	**22.15**	**17.24**	**16.07**	**15.98**	**-6.17**	**-6.39**	**-7.93**
	t-statistic	[4.21]	[5.15]	[4.85]	[4.25]	[-1.61]	[-1.85]	[-2.44]
	excap	0.23	0.23	0.22	0.21			
3	return	**21.80**	**14.71**	**14.64**	**12.88**	**-8.92**	**-8.31**	**-10.53**
	t-statistic	[3.73]	[3.93]	[4.74]	[3.64]	[-1.99]	[-2.00]	[-2.69]
	excap	0.50	0.49	0.48	0.48			
4 (high)	return	**25.10**	**11.39**	**11.57**	**7.97**	**-17.13**	**-16.19**	**-20.60**
	t-statistic	[3.17]	[2.34]	[2.96]	[1.95]	[-2.46]	[-2.53]	[-3.04]
	excap	1.27	1.13	1.09	1.13			

[a] This table shows the average stock returns of sequentially-sorted portfolios. To create the portfolios, stocks are first sorted into portfolios according to the excess capacity proxy (EXCAP); within each excess capacity portfolio, they are then sorted into portfolios according to either the short-term past return (MOM; Panel A), the long-term past return (LTR; Panel B) or the alternative long-term past return (MOM+LTR, Panel C). A detailed description of the sorting variables is given in Table A.1. We use the values of the sorting variables and their quartile breakpoints in month $t-1$ to form the portfolios. Portfolio 1 (low) contains stocks with low values for the sorting variable, and portfolio 4 (high) contains stocks with high values. Conditioning only on stocks from one excess capacity quartile, we also create a spread portfolio that is long on the high past return portfolio and short on the low past return portfolio (High - Low Past Return). The portfolios are equally-weighted, and they held over the entire month t. Mean annualized returns (return) are in bold, and t-statistics (t-statistic), calculated using the Newey and West (1987) formula with $l = 12$, are in square parentheses. The number below the t-statistic is the mean EXCAP value (excap). We report both unadjusted (unadj) and CAPM (CAPM)- or Fama-French/Carhart model-adjusted (FFC) mean returns for the past return spread portfolios. The adjusted returns are the intercepts from a full sample time-series regression of the portfolio return on the market (CAPM) or the market, SMB, HML and MOM (Panels B and C) or the market, SMB, HML and LTR (Panel A, FFC model). The sample period is January 1980-December 2010.

Table 5: Cross-Sectional Estimations[a]

	1	2	3	4	5	6	7	8	9	10
Panel A: Estimates										
MOM	**0.446**	**0.820**			**0.695**	**0.330**	**0.716**			**0.568**
	[1.87]	[3.71]			[2.95]	[1.43]	[3.12]			[2.41]
MOM × REXCAP		**-0.643**			**-0.612**		**-0.666**			**-0.607**
		[-2.68]			[-2.69]		[-2.46]			[-2.31]
LTR			**-0.370**	**-0.063**	**-0.139**			**-0.401**	**-0.164**	**-0.196**
			[-2.31]	[-0.40]	[-0.95]			[-2.57]	[-1.13]	[-1.35]
LTR × REXCAP				**-0.585**	**-0.459**				**-0.449**	**-0.418**
				[-3.70]	[-3.25]				[-2.81]	[-2.69]
BETA	**-0.071**	**-0.075**	**-0.023**	**-0.024**	**-0.074**	**-0.066**	**-0.071**	**-0.023**	**-0.025**	**-0.071**
	[-1.01]	[-1.08]	[-0.30]	[-0.31]	[-1.07]	[-0.95]	[-1.04]	[-0.31]	[-0.33]	[-1.04]
SIZE	**-0.144**	**-0.136**	**-0.081**	**-0.079**	**-0.088**	**-0.144**	**-0.136**	**-0.087**	**-0.085**	**-0.085**
	[-2.03]	[-1.95]	[-1.30]	[-1.29]	[-1.62]	[-2.04]	[-1.98]	[-1.43]	[-1.42]	[-1.58]
BM	**0.293**	**0.306**	**0.214**	**0.218**	**0.214**	**0.292**	**0.306**	**0.207**	**0.211**	**0.209**
	[2.83]	[3.00]	[1.83]	[1.87]	[1.90]	[2.83]	[3.00]	[1.77]	[1.82]	[1.85]
ILLIQ	**0.013**	**0.013**	**0.016**	**0.016**	**0.014**	**0.012**	**0.012**	**0.014**	**0.015**	**0.014**
	[1.46]	[1.53]	[1.83]	[1.84]	[1.86]	[1.36]	[1.42]	[1.67]	[1.71]	[1.76]
REXCAP						**-0.413**	**-0.562**	**-0.524**	**-0.537**	**-0.667**
						[-4.50]	[-5.53]	[-3.78]	[-3.92]	[-5.70]
CONS	**3.153**	**3.044**	**2.409**	**2.371**	**2.343**	**3.367**	**3.327**	**2.755**	**2.728**	**2.633**
	[3.07]	[3.02]	[2.59]	[2.57]	[2.82]	[3.35]	[3.37]	[3.08]	[3.07]	[3.20]
Panel B: Sum of Estimates										
MOM+LTR					**0.557**					**0.371**
					[1.89]					[1.25]
(MOM+LTR) × REXCAP					**-1.071**					**-1.025**
					[-3.42]					[-2.78]

[a] This table shows the estimation results of Fama-MacBeth (1973) regressions of the stock return on several combinations of pricing factors. Panel A gives parameter estimates; Panel B gives the sum of specific parameter estimates (in bold). We use the Newey and West (1987) formula with $l = 12$ to calculate t-statistics (in square parentheses). A description of the analysis variables is in Table A.1. "MOM × REXCAP" ("LTR × REXCAP") is an interaction between the short-term past return (MOM) (the long-term past return (LTR)) and the rank variable based on the excess capacity proxy (REXCAP). We use accounting values from the last fiscal quarter-end that is at least two months in the past. All market variables are based on data up to month $t-1$. The sample period is January 1980-December 2010.

Table 6: Time-Series Analysis[a]

	1	2	3	4	5	6
Panel A: MOM Past Return						
AEXCAP	**-0.141**			**-0.133**		**-0.119**
	[-2.12]			[-2.16]		[-2.11]
ACPUUTL		**-0.194**			**-0.187**	**-0.078**
		[-1.53]			[-1.68]	[-0.84]
NBER			**-0.013**	**-0.007**	**-0.007**	**-0.005**
			[-0.85]	[-0.65]	[-0.54]	[-0.47]
UTS			**-0.023**	**-0.027**	**0.031**	**-0.004**
			[-0.21]	[-0.26]	[0.26]	[-0.03]
UPR			**0.071**	**0.019**	**0.128**	**0.047**
			[0.48]	[0.13]	[0.86]	[0.32]
CONS	**0.066**	**0.046**	**0.007**	**0.064**	**0.046**	**0.074**
	[2.39]	[1.84]	[2.83]	[2.42]	[2.00]	[2.31]
Adj. R^2	4.83%	1.75%	0.29%	4.32%	1.68%	4.30%
Panel B: LTR Past Return						
AEXCAP	**-0.074**			**-0.089**		**-0.078**
	[-2.31]			[-2.91]		[-2.48]
ACPUUTL		**-0.165**			**-0.134**	**-0.063**
		[-2.55]			[-2.02]	[-1.05]
NBER			**-0.005**	**-0.001**	**0.000**	**0.001**
			[-0.69]	[-0.14]	[-0.06]	[0.12]
UTS			**-0.189**	**-0.191**	**-0.150**	**-0.173**
			[-2.40]	[-2.39]	[-1.84]	[-2.12]
UPR			**-0.324**	**-0.360**	**-0.284**	**-0.336**
			[-3.47]	[-3.72]	[-2.89]	[-3.24]
CONS	**0.023**	**0.026**	**-0.008**	**0.030**	**0.020**	**0.038**
	[1.72]	[1.86]	[-2.16]	[2.41]	[1.44]	[2.72]
Adj. R^2	2.10%	2.23%	3.42%	6.44%	4.61%	6.44%
Panel C: MOM+LTR Past Return						
AEXCAP	**-0.143**			**-0.148**		**-0.126**
	[-2.44]			[-2.84]		[-2.70]
ACPUUTL		**-0.267**			**-0.240**	**-0.124**
		[-2.28]			[-2.26]	[-1.48]
NBER			**-0.014**	**-0.007**	**-0.006**	**-0.004**
			[-1.01]	[-0.74]	[-0.53]	[-0.40]
UTS			**-0.138**	**-0.142**	**-0.068**	**-0.106**
			[-1.25]	[-1.34]	[-0.59]	[-0.95]
UPR			**-0.191**	**-0.250**	**-0.119**	**-0.204**
			[-1.52]	[-2.09]	[-0.92]	[-1.61]
CONS	**0.057**	**0.053**	**-0.002**	**0.061**	**0.048**	**0.077**
	[2.34]	[2.22]	[-0.61]	[2.72]	[2.20]	[2.87]
Adj. R^2	5.18%	3.75%	0.82%	6.10%	3.39%	6.48%

[a] This table shows the results of time-series regressions of the momentum (MOM; Panel A) or long-term reversal effects (LTR or MOM+LTR; Panels B and C, respectively) on various sets of predictor variables. The effects are equal to the returns of spread portfolios that are long on stocks with a past return above the third quartile, and short on stocks with a past return below the first quartile. The portfolios are formed according to the values of the sorting variables and their quartile breakpoints in month $t-1$. They are equally-weighted and held over month t. The predictor variables are: the cross-sectional mean of the firm-level excess capacity proxy obtained from the stochastic frontier model (AEXCAP); the cross-sectional mean of industry-specific survey capacity under-utilization, weighted by the number of firms per industry (ACPUUTL); a dummy variable equal to one during NBER-defined recessions and zero otherwise (NBER); the return spread between 20-year and one-year government bonds (UTS); and the return spread between high-yield and AAA-rated corporate bonds (UPR). All predictor variables are lagged by two months. Estimates are in bold. T-statistics, calculated using the Newey and West (1987) formula with $l = 12$, are in parentheses. 'Adj R^2' is the adjusted R-squared. The sample period is January 1980-December 2010.

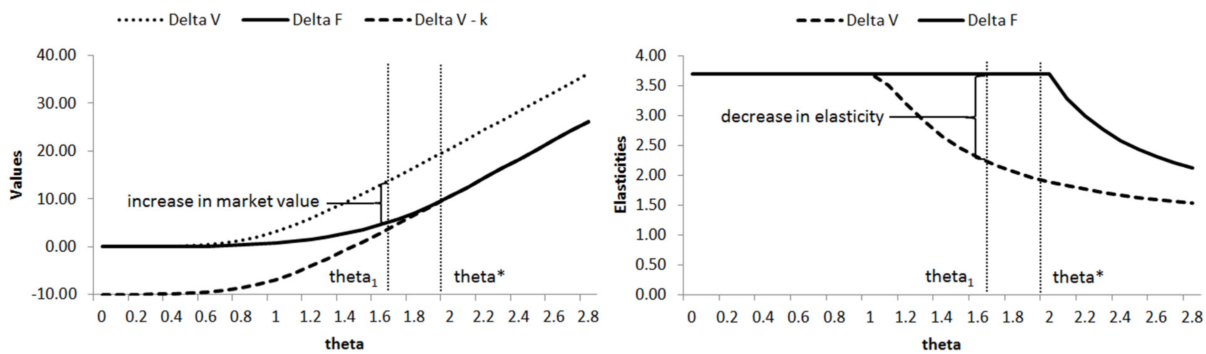


Figure 1: The graph plots the market values and elasticities of the production option (Delta V) and the option to build the production option (Delta F) against the stochastic variable driving demand, θ. Both options are on the first unit of output (i.e., v=1). The market values are shown in the left panel, and the elasticities are in the right panel. The base case values are as follows. The stochastic process parameters, α and σ, are 0.05 and 0.10, respectively. The elasticity of demand, γ, is 0.50, and both cost function parameters, c_1 and c_2, are zero. The cost of one unit of capital, k, is 10. The expected return of the asset perfectly correlated with demand, μ, is 0.10. The risk-free rate, r, is 0.04. The option to produce output should be exercised if θ is above one, and the option to build the production option should be exercised at θ equal to two.

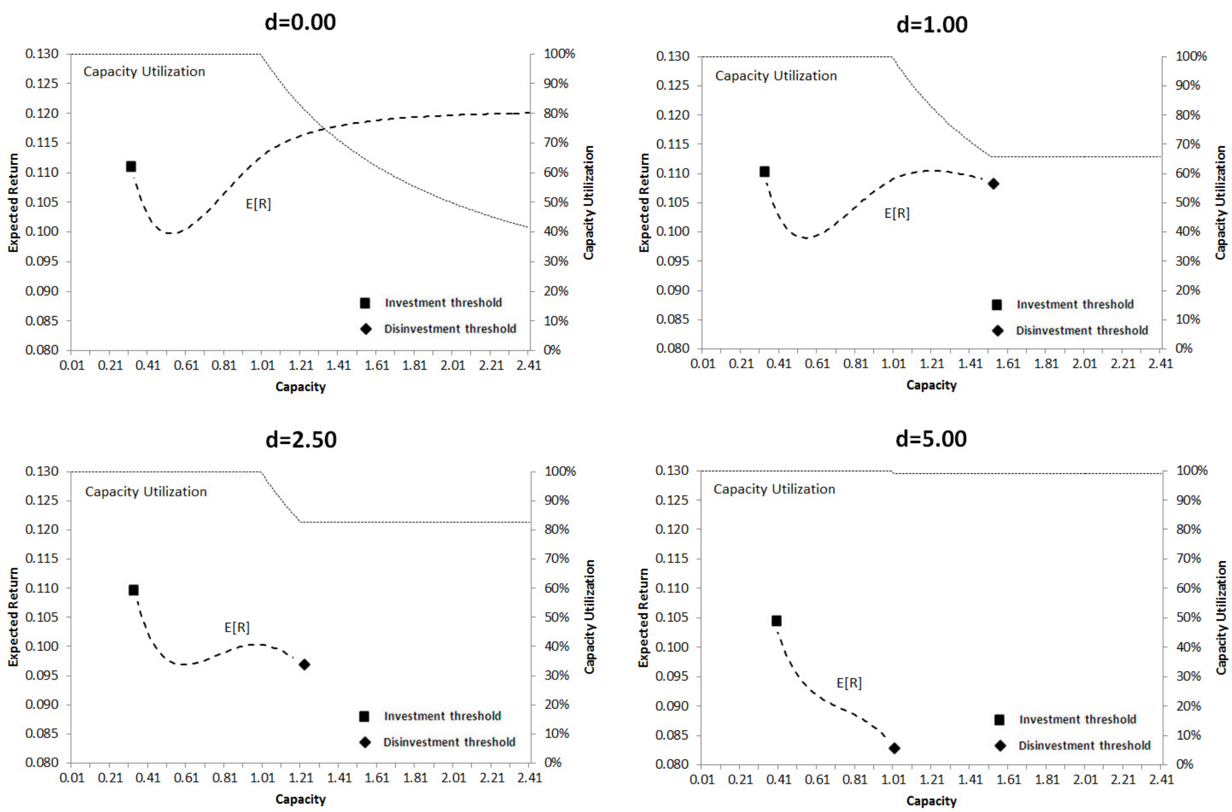


Figure 2: The graph plots the expected return (left y-axis) and capacity utilization (right y-axis) against capacity (x-axis), assuming that capacity can be sold at a unit price of d. The current value of the stochastic process, θ, is 1.00, and the stochastic process parameters, α and σ, are 0.05 and 0.10, respectively. The elasticity of demand, γ, is 0.50, and both cost function parameters, c_1 and c_2, are zero. The cost of one unit of capital, k, is 10. The demand risk premium, μ, is 0.10. The risk-free rate, r, is 0.04.

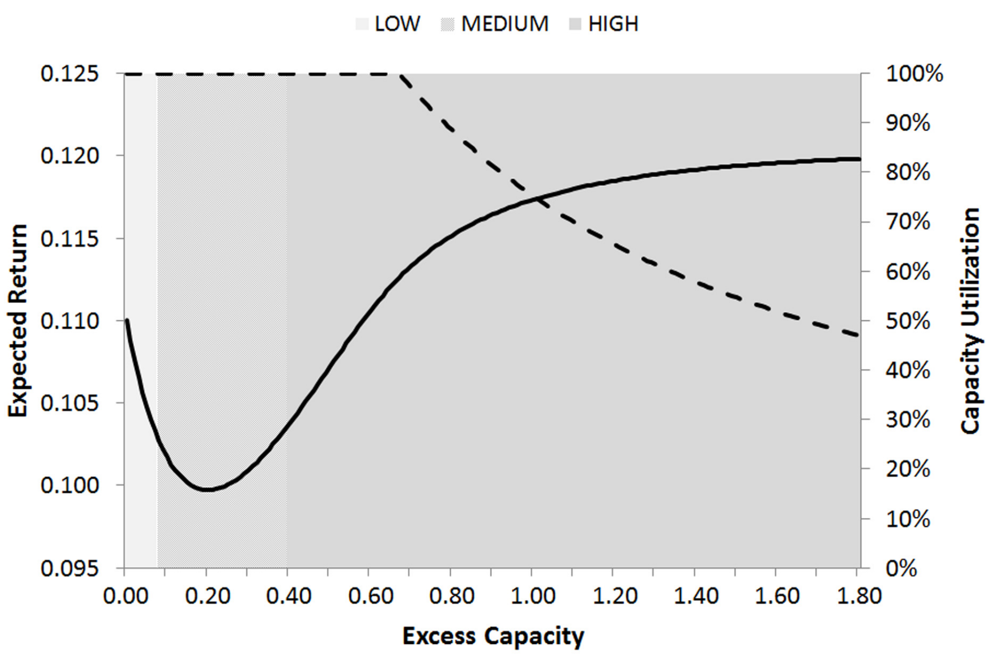


Figure 3: The graph plots the expected return (on the left y-axis) and capacity utilization (on the right y-axis) against excess capacity (on the x-axis). The graphs divides excess capacity into three regions: low (< 0.05), medium (0.05-0.40), and high (> 0.40). The graph assumes that investments are completely irreversible. We use the base case values for all model inputs to create the graph. The base case values are as follows: The current value of the stochastic process, θ, is 1.00, and the parameters governing its evolution, α and σ, are 0.05 and 0.10, respectively. The elasticity of demand, γ, is 0.50, and both cost function parameters, c_1 and c_2, are zero. The cost of one unit of capital, k, is 10. The expected return of the asset perfectly correlated with demand, μ, is 0.15. The risk-free rate, r, is 0.04.

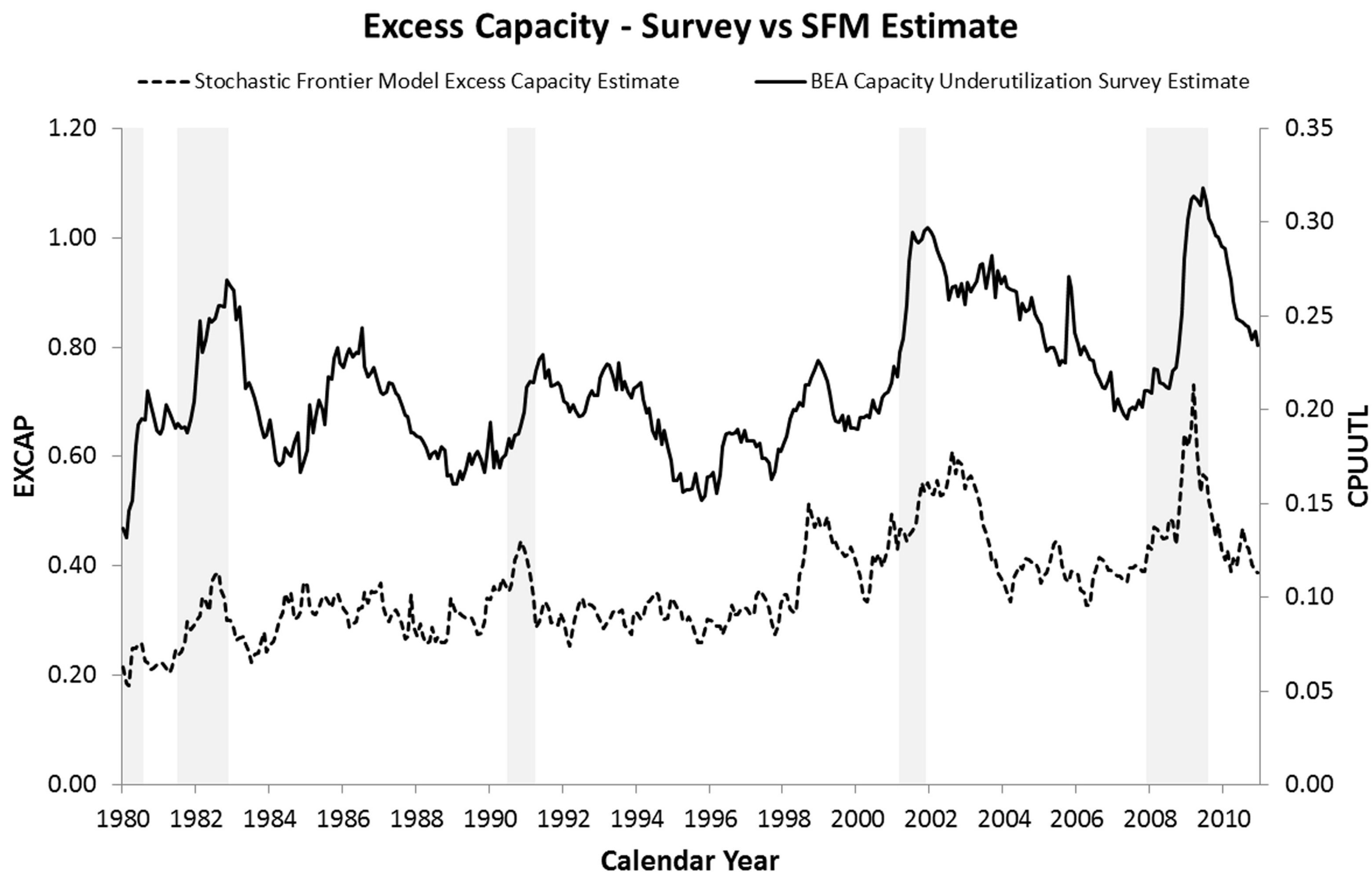
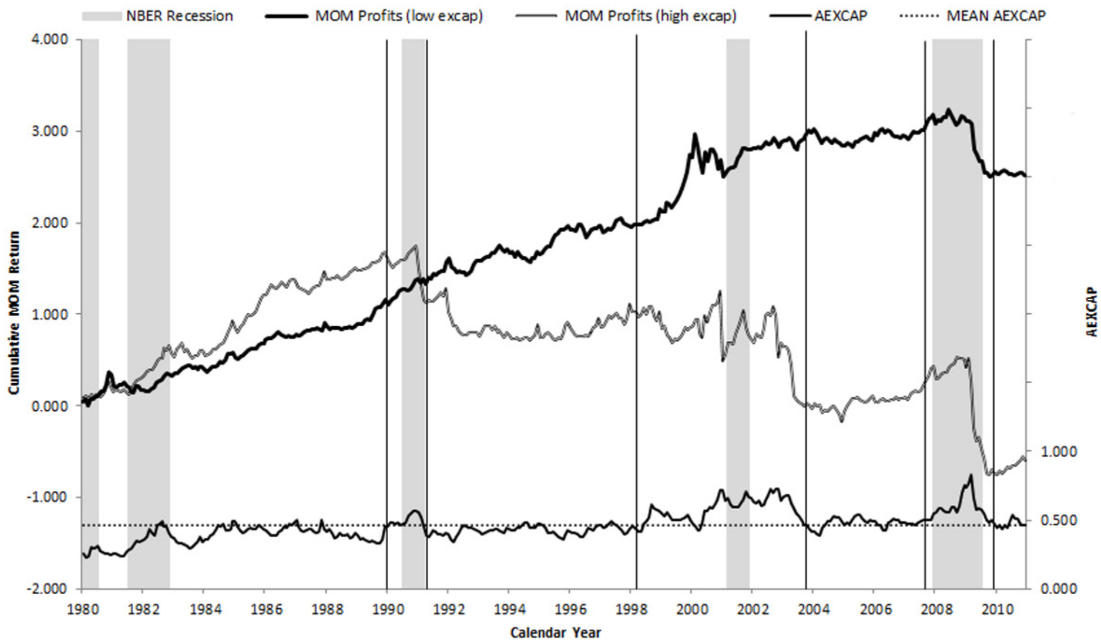
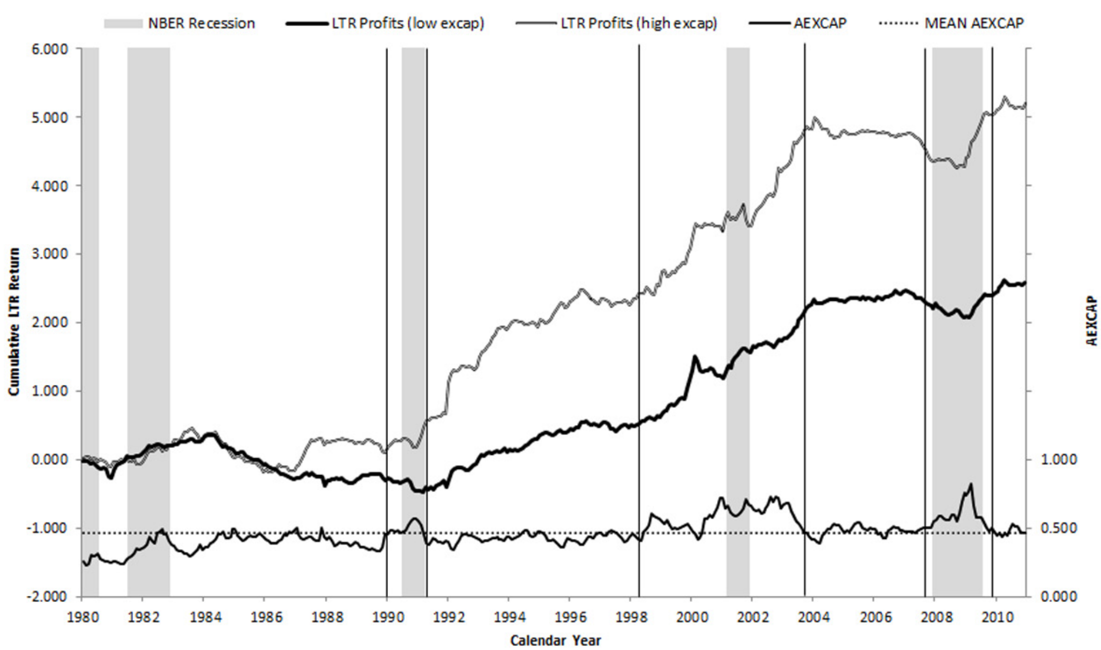


Figure 4: The graph plots the cross-sectional median of the excess capacity estimate (EXCAP) and the capacity under-utilization estimate obtained from surveys of the Bureau of Economic Analysis (BEA; CPUUTL) over time. To enhance comparability, the excess capacity median is based on only those firms operating in industries surveyed by the BEA. We ensure that both measures were observable by investors at the time (i.e., CPUUTL is lagged by one month). The sample period is January 1980-December 2010.

Panel A: MOM Profitability



Panel B: LTR Profitability



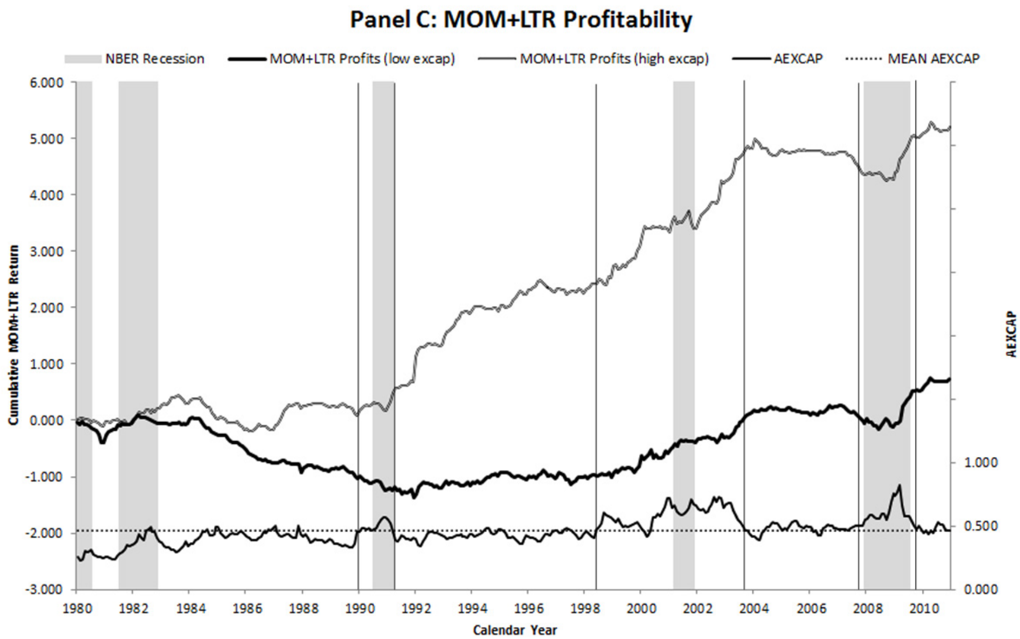


Figure 5: The graph plots the cumulative (added-up) return of momentum and long-term reversal spread portfolios over the sample period. The spread portfolios in Panels A, B, and C rely on MOM, LTR, and MOM+LTR as sorting variable, respectively. In Panel A, the spread portfolio is long those stocks in the highest past return quartile in month $t-1$ and short those in the lowest past return quartile; in Panels B and C, the spread portfolio is long those stocks in the lowest past return quartile in month $t-1$ and short those in the highest past return quartile. The spread portfolios are formed from either stocks in the highest (high excap) or the lowest EXCAP quartile (low excap). They are equally-weighted and held over month t. At the bottom of each panel, we also show aggregate excess capacity, defined as the cross-sectional mean of EXCAP in a specific month, and the time-series mean of aggregate EXCAP. The shaded areas denote NBER-defined recession periods, the vertical lines periods in which aggregate excess capacity was substantially above its time-series mean. The sample period is January 1980 to December 2010.