Inflexibility and Stock Returns

Lifeng Gu
University of Hong Kong

Dirk Hackbarth
Boston University

Tim Johnson
University of Illinois at Urbana-Champaign

Investment-based asset pricing research highlights the role of irreversibility as a determinant of firms' risk and expected return. In a neoclassical model of a firm with costly scale adjustment options, we show that the effect of scale flexibility (i.e., contraction and expansion options) is to determine the relation between risk and operating leverage: risk increases with operating leverage for inflexible firms, but decreases for flexible firms. Guided by theory, we construct easily reproducible proxies for inflexibility and operating leverage. Empirical tests provide support for the predicted interaction of these characteristics in stock returns and risk. (*JEL* D31, D92, G12, G31)

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Do more valuable real options make stock returns safer and thereby lower expected returns? Intuition suggests that the risk a firm's owners bear decreases with its flexibility to respond to changes in operating conditions. Likewise, intuition suggests that risk increases as a firm's fixed costs rise, relative to sales, as the result of operating leverage. In a neoclassical model of a firm with both scale flexibility and operating leverage, we show that neither intuition is strictly correct. Instead, we show that risk and returns are driven by an interaction of these two characteristics. Empirical tests support the model's asset pricing implications.

This study is among the first to explore the effect of cross-firm differences in operational flexibility for the risk and expected return characteristics of a

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firm's equity.[1] Although the real options literature has long recognized that differences in option exercise costs imply important differences in investment policies (see, e.g., Abel et al. 1996; Abel and Eberly 1996), the implications of this heterogeneity has received little attention in asset pricing research. Moreover, empirical research on corporate investment documents substantial differences across firms in the purchase and resale prices of physical capital.[2] These differences imply variation in the value of real options to increase or decrease firm scale.

We utilize a dynamic model of a firm with assets-in-place (which entail fixed operating costs), contraction options (to scale back the firm's asset base in bad times), and expansion options (to scale up the firm's asset base in good times). The model is both rich enough to encompass ex ante heterogeneous firms, and yet simple enough to reveal general implications of this heterogeneity for equity returns. The key state variable is the firm's asset base scaled by its productivity. As productivity exogenously varies, the state variable evolves continuously until the firm chooses to discretely increase or decrease its assets. Each firm will optimally choose an upper and a lower boundary at which these scale adjustments are made. When adjustment is more costly, the firm will wait longer before acting. Thus, an important implication of the model is that inflexibility can be summarized by the range of scaled productivity.

In the model, real options may increase or decrease risk. Adjusting the firm's scale means exchanging (riskless) cash for (risky) assets. Exercising the option to contract (akin to a put option) thus attenuates firm risk, whereas exercising the option to expand has the opposite effect. Prior to exercise, firm risk will reflect the likelihood of these scale adjustments. So, comparing two firms, if one has lower contraction costs than the other, it is more likely to exercise its put option, making it less risky. However, by the same logic, a firm with lower expansion costs is more risky. In both cases, lower adjustment costs make the firm more flexible. Hence, perhaps contrary to intuition, flexibility is not unambiguously associated with lower risk.

Whereas the level of the risk premium is not, in general, increasing in inflexibility, the sensitivity of the risk premium to changes in scaled productivity (the state variable) is. This is the primary implication that we will test. If the firm had no real options, productivity declines would always raise systematic risk because of increased operating leverage caused by fixed costs. But both expansion and contraction options work the opposite way: decreasing firm risk as productivity declines, despite the increase in operating leverage. Thus, the implication is equivalent to saying that the degree of flexibility drives the sign

[1] The investment-based asset pricing literature has typically focused on the properties of collections of ex ante identical firms that differ only in their history of idiosyncratic shocks. See, for example, Berk, Green, and Naik (1999), Carlson, Fisher, and Giammarino (2004), Zhang (2005), Cooper (2006), and Li, Livdan, and Zhang (2009).

[2] See, for example, MacKay (2003), Balasubramanian and Sivadasan (2009), Chirinko and Schaller (2009), and Kim and Kung (2017).

of the relation between operating leverage and expected return. We find this real option effect can be economically large: using plausibly calibrated parameters, simulated panels of firms that differ in scale adjustment costs indeed reveal both positive and negative relations between operating leverage and expected stock returns.

Turning to the data, we construct first a firm-level proxy for inflexibility that is guided by the theory and is easy to implement. As discussed above, the model implies that a firm's inflexibility is directly linked to the inaction region, that is, the range of profitability that it experiences. We therefore measure a firm's inflexibility as the historical range (maximum minus minimum) of its operating costs-to-sales ratio, scaled by the volatility of the firm's sales growth.[3] In general, this range will be affected by many dimensions of flexibility, such as the ability to alter or transform factor intensity, product mix, pricing strategy, and technology. Although these dimensions are omitted from the model, they have in common the implication that less flexible firms will exhibit a wider range.[4] Second, the model implies that operating leverage is not a fixed firm characteristic, but one that varies with the ratio of quasi-fixed costs (i.e., those that do not scale with output) to sales. We therefore assess a firm's operating leverage each year using regression-based estimates of quasi-fixed costs. Within the model, we verify that our measurement strategies for both quantities are theoretically sound and feasible in the sense that applying them within simulated panels of firms yields numbers that are strongly correlated with the population values they are designed to estimate.

Our inflexibility measure is new, so we provide direct evidence supporting its interpretation as capturing adjustment costs. We first show that it is positively related to an array of other proxies for factor adjustment frictions that have been used in the empirical literature. We then show that investment of more flexible firms – as captured by our measure – responds more positively to Tobin's q than that of inflexible firms. Moreover, our inflexibility measure outperforms most available alternatives in investment regressions. Hence it represents a valid measure of inflexibility and also a valuable contribution to the empirical investment literature in its own right.

With these two measures, we take the model's asset pricing implication of an interaction of these characteristics in stock returns and risk to the data. Portfolios formed via two-way independent sorts on inflexibility and operating leverage indeed reveal the predicted return pattern, namely, operating leverage increases expected returns *more* for more inflexible firms. Our baseline results show that the monthly excess returns for the high-minus-low operating leverage

3 Fischer, Heinkel, and Zechner (1989) use a similar range measure to test a dynamic capital structure model.

4 Our work is related to the literature on nominal rigidities, an aspect of adjustment inflexibility. Recent contributions studying implications of price and wage rigidities for asset pricing are Uhlig (2007), Chen, Kacperczyk, and Ortiz-Molina (2011), Favilukis and Lin (2015), Li and Palomino (2014), Weber (2015), and Gorodnichenko and Weber (2016).

portfolio for most flexible and least flexible firms are 30 and 88 basis points, respectively. The difference between these two numbers is significant both statistically and economically. In Fama and MacBeth (1973) regressions using firm-level returns, these findings are robust to the inclusion of standard controls and to alternative measurement of operating leverage. Specifically, the model predicts a positive interaction effect of operating leverage with inflexibility. When both variables are expressed in percentile rank, the estimated interaction effect is about 100 basis points per month. Additional robustness tests using industry-based measures of flexibility and firm loadings on an inflexibility factor, provide further support for the main findings.

Finally, we also examine the model's predictions for the second moments of equity returns. Holding fundamental risk constant, theory implies that systematic and total risk should exhibit the same behavior as expected returns. Indeed, the patterns of portfolio return volatility and average portfolio beta across portfolios sorted by inflexibility and operating leverage resemble the ones from the return test. Specifically, these double sorts show that the relation between portfolio return volatility (or average portfolio beta) and operating leverage becomes increasingly positive as inflexibility increases.

1. Model

To study the expected return and risk implications of ex ante differences in operating flexibility, we employ the model developed in Hackbarth and Johnson (2015) (hereafter HJ). The model describes the evolution of a firm's optimal investment and disinvestment policy in response to permanent productivity shocks, in a continuous-time, partial-equilibrium economy. The model embeds a natural notion of firm flexibility, and is tractable enough to enable ready exploration of the role of heterogeneous firm characteristics in determining expected return patterns in the cross-section.[5] After briefly reviewing the model and describing our interpretation of flexibility, we assess the model's implications for the joint relation between flexibility, operating leverage, and expected return or risk. We illustrate the magnitudes of the implied effects in plausibly calibrated panel simulations.

1.1 Framework

HJ consider a firm with repeated expansion and contraction options to alter its scale (and operating expenses) in response to productivity shocks, subject to adjustment costs. That work follows the production-based asset pricing literature by viewing the firm's scale as equivalent to its physical capital. The economic logic of the HJ model is not confined to plant and equipment, however. Here we suggest a broader interpretation, and think of the firm's

[5] HJ fully characterize a firm's risk premium as a function of a single state variable. The model solution does not, however, provide an analytical mapping between fixed firm characteristics and the risk premium.

scale as encompassing the composite of productive factors that the firm has in place. Just as accounting rules view long-term leases as capitalized assets, so one could view long-term contracts for other inputs (human capital, labor, raw materials and other supplies, franchise agreements) as being assets-in-place in three senses: (1) they are needed to generate output; (2) their cost contains a fixed component that does not scale with output; and (3) their quantity is costly to adjust. Other assets, such as knowledge, organizational capital, and intellectual property, may share these properties.

Given this interpretation, A denotes the firm's composite scale, or the total assets-in-place, and the firm's profit flow per unit time (i.e., net sales minus quasi-fixed operating costs) is

$$\Pi_t = \theta_t^{1-\gamma} A_t^{\gamma} - m A_t, \tag{1}$$

where $\gamma \in (0,1)$ captures returns to scale and $m > 0$ denotes the operating cost per unit of A. Unless adjusted by the firm, A follows $dA/dt = -\delta A$, where $\delta \geq 0$ captures the generalized depreciation, or retirement rate of the asset base.

The productivity process θ evolves as a jump-diffusion with drift μ, volatility σ, and obsolescence rate η. The stochastic differential equation is as follows:

$$d\theta/\theta = \mu\, dt + \sigma\, dW^{\theta} - dN, \tag{2}$$

where W is a standard Wiener process and N is a Poisson process whose intensity per unit time is η.[6] We restrict attention to an all equity financed firm without external financing frictions.

The economy is characterized by a stochastic discount factor, Λ, with a fixed drift, r (the riskless interest rate), and fixed volatility, σ_{Λ} (the maximal Sharpe ratio). That is, Λ obeys the stochastic differential equation:

$$d\Lambda/\Lambda = -r\, dt + \sigma_{\Lambda}\, dW^{\Lambda}. \tag{3}$$

The constant coefficients imply that the macroeconomic environment is not a source of variation in the firm's business conditions. The model thus does not capture business cycle effects in the cost of capital. The correlation between dW^{Λ} and dW^{θ}, represented by ρ, parameterizes the systematic risk of the firm's earnings stream. We assume $\rho < 0$, that is, the risk premium is positive.

The firm's real options to increase or decrease scale in response to shocks to profitability determine its flexibility. More flexible firms adjust their scale more often and hence operate, on average, closer to the optimal scale implied by profitability. Hence excursions away from the optimal scale (i.e., operating ranges) are smaller than those of otherwise identical but less flexible firms. The value of the firm's real options is dictated by the cost of these adjustments. The model assumes the firm faces both quasi-fixed and variable costs for either

[6] Note that the change, dN, for this process is zero until a jump, at which point $dN = 1$ so that $d\theta = -\theta$, and the firm's production terminates.

upward or downward adjustments. The cash cost to investors of increasing A by ΔA is represented by $P_L\ \Delta A$, where $P_L \geq 1$, and the cash extracted from decreasing A by ΔA is $P_U\ \Delta A$, where $P_U \leq 1$. In addition, the quasi-fixed cost of upward and downward adjustments are written $F_L\ \theta^{1-\gamma}\ A^{\gamma}$ and $F_U\ \theta^{1-\gamma}\ A^{\gamma}$, respectively, with $F_L > 0$ and $F_U > 0$. These components are proportional to the firm's net revenue at the time of the adjustment and can be viewed as capturing the forgone revenue resulting from diversion of scarce internal resources, such as managerial time.

When thinking of A as physical capital, it is natural to view P_L as the purchase price, for example, of machinery, with $P_L > 1$ reflecting installation frictions. That is, there is a deadweight loss of $(P_L - 1)\ \Delta A$ of expanding the firm. Likewise P_U may be viewed as the resale price, and contraction entails the loss of $(1 - P_U)\ \Delta A$ as the result of costly disposal. Thus, the firm's real flexibility decreases if the purchase price, P_L, is higher or the resale price, P_U, is lower, because either one results in an increased deadweight cost of responding to changes in productivity. The case $P_U = 1$ implies that assets can be costlessly liquidated. The case $P_U = 0$ is similar to scale-irreversiblity in the sense that nothing is recovered upon contractions.[7] Further, $P_U < 0$ is also conceivable because of the penalty costs of terminating long-term contracts, clean-up costs, etc.[8]

The firm's objective is to choose an adjustment policy for firm scale, A_t, to maximize its market value of equity. HJ show that the re-scaled productivity variable $Z_t \equiv A_t/\theta_t$ is a sufficient statistic for the firm's problem, and therefore that the optimal policy may be characterized by four scalar constants: upper and lower adjustment boundaries (represented by U and L) for Z, together with optimal contraction and expansion amounts undertaken upon hitting each of these boundaries. That is, if Z hits U at time t, the adjustment is to an interior optimal target level $Z = H < U$, which corresponds to a contraction of $\Delta A = (U - H)\theta_t$. When Z hits L, the adjustment is to an interior optimal target level $Z = G > L$, which corresponds to an expansion of $\Delta A = (G - L)\theta_t$. Recall that decreases in Z correspond to good news (high productivity that justifies an expansion of the firm's scale), whereas increases in Z correspond to bad news (low productivity that calls for a contraction in the firm's scale). HJ show the solution is stationary and scale-invariant in the sense that the firm lives on the Z interval $[L, U]$ regardless of the magnitude of A. For reference, Table 1 summarizes the model notation.

Let $J(\theta, A)$ denote the value of the firm's equity. Given the optimal policy, HJ show that, subject to some regularity conditions, the rescaled equity value,

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[7] Irreversibility is usually interpreted in the investment literature (see, e.g., Cooper 2006) to imply that the firm's *only* contraction option is to shut down entirely, that is, $\Delta A = A$, which our model does not impose.

[8] With the broader interpretation of assets-in-place, A, that we have suggested, the frictionless case $P_L = P_U = 1$ may not always be the natural benchmark, because expanding the scale of labor inputs, for example, might entail no cash outlay by the firm's owners. Still, in this case, the total value of the firm's real options would decrease with the difference $P_L - P_U$.

Table 1
Model notation

Quantity	Symbol
Firm scale (policy)	A_t
Returns-to-scale	γ
Scale decay	δ
Quasi-fixed operating costs	m
Productivity (state)	θ_t
Growth rate of θ	μ
Volatility of θ	σ
Expected lifetime of firm	$1/\eta$
Rescaled productivity	$Z_t \equiv A_t/\theta_t$
Expansion boundary (rescaled)	L
Expansion target (rescaled)	G
Contraction target (rescaled)	H
Contraction boundary (rescaled)	U
Proportional expansion price	P_L
Proportional contraction price	P_U
Fixed expansion cost	F_L
Fixed contraction cost	F_U
Riskless interest rate	r
Pricing kernel volatility	σ_Λ
Systematic θ risk	$\rho\sigma$
Market price of θ risk	π_θ

$V(Z)=J(\theta,A)/\theta$, is given by

$$V(Z)=B\ Z^{\gamma}-S\ Z+D_N\ Z^{\lambda_N}+D_P\ Z^{\lambda_P}, \tag{4}$$

where λ_N and λ_P are the negative and positive roots of a quadratic equation (see Appendix A), B and S are functions of the model parameters, so that BZ^{γ} and SZ capture, respectively, current values of net sales and operating costs. The coefficients D_N and D_P determine, respectively, the market values of the firm's expansion and contraction options. The latter two constants together with the policy boundaries L, G, H, and U are characterized by a system of six algebraic equations (see Appendix A). Although not solvable analytically in terms of the firm parameters, solutions are readily obtainable numerically.

$\pi_\theta=-\rho\sigma\sigma_\Lambda$ denotes the market price of θ risk. Then the firm's expected excess return on equity (the risk premium) and the instantaneous volatility of equity returns are given by

$$EER(Z)=\pi_\theta(1-ZV'/V) \tag{5}$$

and

$$VOL(Z)=\sigma(1-ZV'/V). \tag{6}$$

The firm's return on assets $ROA(Z)$ is given by $Z^{\gamma-1}-m$. The elasticity of ROA with respect to productivity shocks—a common definition of operating leverage—is $(1-\gamma)/(1-mZ^{1-\gamma})$.[9] The denominator of that expression is not

[9] The elasticity of return on assets with respect to productivity shocks is equal to $\frac{dROA(A/\theta)}{d\theta}\times\frac{\theta}{ROA(A/\theta)}$.

guaranteed to be positive, hence we prefer to define operating leverage as the ratio of quasi-fixed costs to sales, $QFC(Z)=mZ^{1-\gamma}$. This quantity is time-varying for each firm, and its average level depends on several factors: the firm's optimal choice of adjustment points; the parameters m and γ; and the growth rate of the state variable Z, which is exogenous.[10]

1.2 Hypothesis development

To explore empirically the effect of flexibility on firm risk and expected return, the first challenge is to measure flexibility. In the context of the model, it is clear that flexibility means the ability to adjust scale with low adjustment costs. Scale adjustment costs are not directly observable. However, from the model's depiction of optimal firm policies, we can plausibly map firm behavior into a proxy that summarizes flexibility.

Without adjustment costs, the firm will always set A to the value $(m/\gamma)^{1/(\gamma-1)}\theta$ to maximize the profit function (1) for a given productivity level θ. With adjustment costs, the firm will pursue the discrete adjustment policy described above. Intuitively, as adjustment costs increase, the firm will allow θ to wander farther from this optimal point before incurring the deadweight losses to bring the ratio Z back towards optimality. Thus, higher inflexibility translates directly into a wider inaction region $[L,U]$. An implication of the model, therefore, is that a summary statistic for scale inflexibility is the relative distance between the adjustment boundaries, $\log(U/L)$, standardized by the volatility of the firm's productivity process, σ.[11] The width of that inaction region also describes the observed range of firm profitability and operating leverage, because these are monotonic functions of Z. These model-implied properties of optimal inaction regions are the basis for the empirical identification strategy described in the next section.

To analyze the cross-sectional asset pricing implications, we can use the model to directly solve for the risk premium function $EER(Z)$, for the return volatility function $VOL(Z)$, as well as for the stationary distribution of Z for firms of differing degrees of flexibility.[12]

The key characteristics of the expected excess return function $EER(Z)$, derived in HJ, follow from the superposition of opposing effects due to (1) assets-in-place and (2) expansion and contraction options. The risk from assets-in-place monotonically increases with Z due to the increasing degree of operating leverage: as Z rises and profitability falls, quasi-fixed production costs magnify the exposure of investor profits to fundamental shocks. By contrast, the risk from both real options declines with Z: in response to good

[10] By Ito's lemma, the drift of $\log(Z)$ is $-\mu-\delta+\sigma^2$.

[11] The firm's inaction region scales with σ because uncertainty delays optimal exercise of the firm's real options. We standardize our measure because this effect is not directly related to the costs of adjustment.

[12] Given (5) and (6), the instantaneous stock return volatility, $VOL(Z)$, can be expressed as $-EER(Z)/(\rho\sigma_\Lambda)$, so it inherits the properties of expected returns discussed in this section.

news (falling Z), expansion options become closer to exercise and thus increase investor exposure to productivity shocks; whereas bad news (rising Z) brings contraction options closer to exercise, which lowers investor exposure to these shocks and hence to priced risk.

Thus, in comparing firms, the primary comparative static implication of the model concerns the *slope* of the risk premium function, $EER(Z)$, rather than its *level*. And the key driver of this slope is the *relative value* of the firm's real options. Here we see the direct connection with flexibility: lower scale adjustment costs imply more valuable real options, and thus a greater contribution to the risk premium function from these options than from assets-in-place. In addition, for flexible firms the range between option exercise points (U and L) is narrow. One or the other option is usually close to exercise, hence the option-driven component of risk (downward sloping in Z) dominates. For inflexible firms, because the inaction region is wide, both options are typically far from exercise. So, over most of their range of Z, risk is determined by assets-in-place and hence upward sloping in Z.

In bringing these observations to the data, another issue arises from the unobservability of the state variable Z. Because the model only encompasses a single dimension of within-firm variability, essentially all measures of current operations are monotonic transformations of Z. In line with the discussion here, the salient feature of variation in Z is the changing exposure to fundamental risk incurred as the result of changes in operating leverage. Our empirical approach will thus attempt to measure the time-varying ratio of quasi-fixed costs to sales.

Figure 1 illustrates how a firm's scale flexibility affects the relation between risk premiums, $EER(Z)$, and operating leverage, $QFC(Z)$, as the state variable Z changes.

The left panel shows the effect of varying the resale price parameter, P_U, while holding all other firm parameters fixed. As the plot illustrates, making the firm's technology more inflexible by lowering the resale price, has two effects. First, as just emphasized, it raises the *average slope* of the curve: expected excess returns rise steeply with operating leverage (at least over the middle part of the graph) for firms with nearly irreversible assets. Higher P_U values result in the average slope changing sign. Second, as P_U declines and hence inflexibility increases, the *operating range* on the horizontal axis increases: the firm chooses to increase U, delaying exercise of its contraction option. Thus, as observed above, the inaction region between the option exercise points (U and L) increases with inflexibility.

The expected return pattern for low P_U firms is consistent with existing models in the literature based on irreversible investment (see, e.g., Cooper 2006). Less appreciated, however, is the fact that for firms with even a mild degree of reversibility, the average slope of the risk profile is negative: the firm's equity becomes safer as profits decline and operating leverage increases. For such a firm, the contribution of the contraction option actually overwhelms the effect of operating leverage. Intuitively, the contraction option is the right

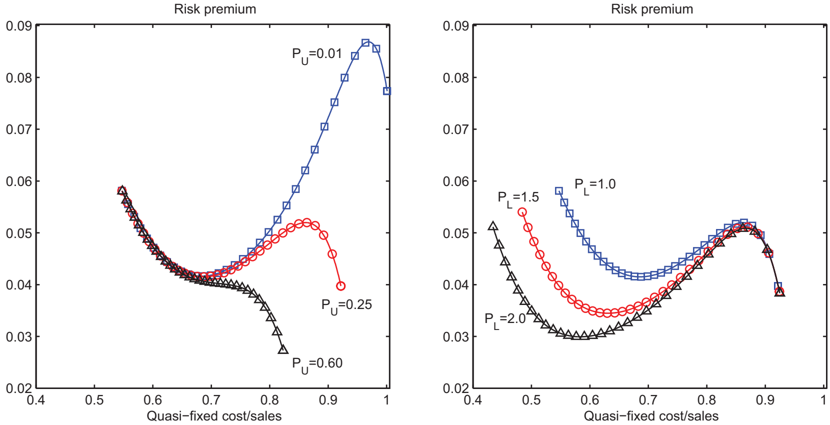

Figure 1
Effect of resale price and purchase price
The left panel shows expected excess returns for firms with resale prices of $P_U = 0.01$ (plotted as squares), $P_U = 0.25$ (circles), and $P_U = 0.6$ (triangles) and a purchase price of $P_L = 1.0$. The right panel shows expected excess returns for firms with purchase prices $P_L = 1.0$ (squares), $P_L = 1.5$ (circles), and $P_L = 2.0$ (triangles) and a resale price of $P_U = 0.25$. In both panels, the horizontal axis is the ratio of quasi-fixed cost, mA, to net sales, $\theta^{1-\gamma} A^{\gamma}$. The other firm parameters are $\gamma = 0.85, m = 0.4, \delta = 0.1, F_L = 0.05, F_U = 0.05, \mu = 0.05, \sigma = 0.3$, and $\rho = -0.25$, and the pricing kernel parameters are $r = 0.04$ and $\sigma_\Lambda = 1.0$.

to exchange risky assets for safe cash, and this option will be exercised quickly upon a deterioration in profitability.[13] Notice also that the effects in the left panel can be economically large. Moving from left to right, the risk premium for the inflexible firm increases from about 6% to almost 9%, whereas that of the flexible firm decreases from 6% to below 3%.

The discussion shows the crucial role of the reversibility parameter, P_U, in determining the relative contribution of the contraction option to firm risk. Likewise, the key parameter determining the strength of the expansion option is the installation cost parameter, P_L. The right panel in Figure 1 exhibits the effect of varying it. As with the left panel, it is again the case that a less flexible firm (higher P_L) exhibits a steeper (or more positive) average increase in risk premium with operating leverage. Again, too, a less flexible firm inhabits a wider range on the horizontal axis: the firm optimally chooses a lower L.

Comparing the two panels, the variation due to the expansion cost P_L is less dramatic than that due to the contraction cost P_U. This conclusion is broadly true over a large range of parameter values. Also true numerically is that the fixed component of adjustment costs have much less impact on firm risk profiles (and on the width of the inaction region) than the variable components.

[13] In a simpler model, Guthrie (2011) shows the negative dependence of expected returns on operating leverage for the case of a firm with a one-time abandonment option, but otherwise fixed scale. The intuition in this case is identical to that in HJ. Moreover, the idea is related to the effect in Garlappi, Shu, and Yan (2008) and Garlappi and Yan (2011), who document that firms approaching bankruptcy experience decreasing risk premia if the absolute priority rule is violated, thereby allowing equity holders to extract recoveries.

For reasonable ranges of variation of F_L and F_U, the induced effects on flexibility and risk are second order.

There is another interesting observation from the right panel of Figure 1: the average *level* of the *EER* curves decreases as P_L increases. Although the variation is not large, in this case, higher inflexibility is not unconditionally associated with higher equity risk. This finding runs counter to the conventional view that firms utilize their real options to buffer investors' exposure to exogenous profitability shocks. Although this *is* true for the contraction options in the left-hand panel (that represent put options on the firm's risky assets), expansion options are call options on the firm's risky assets and hence raise exposure to priced risk. Thus making growth options more valuable via lowering the purchase price P_L, raises the required return on equity, while conferring increased operating flexibility. Therefore, the model offers no unambiguous prediction as to whether or not there should be an unconditional relation in the data between measures of firm operating flexibility and average stock returns.[14]

It is also worth pointing out that the more flexible firm in the right panel operates at a *lower* average level of profitability and hence at a *higher* average level of fixed costs than the less flexible firm. This provides another counterexample to conventional wisdom that might suggest that the degree of "cost stickiness" (or average $QFC(Z)$) measures operating flexibility.

1.3 Magnitudes

To gauge the quantitative magnitude of the effect identified above (i.e., the relation between expected return and operating leverage being conditional upon inflexibility), we simulate panels of model firms that differ ex ante in their flexibility, and then differ ex post in the realization of their productivity (and hence operating leverage). Within these panels, we then run tests that closely parallel our subsequent empirical work.

Specifically, the experiment fixes the model parameters to be those estimated by HJ to most closely match an array of operating and financial moments, including mean and interquartile range of profitability and book-to-market, in the population of U.S. listed firms.[15] We then augment their set of baseline parameter values to include heterogeneity in the resale price parameter P_U, which has the most significant effect on the shape of the expected return profile. The simulation uses the values $P_U = [0.01, 0.13, 0.25, 0.50, 1.00]$ assigning equal weight to each firm type. (Results incorporating two-dimensional heterogeneity in P_U and P_L are similar.) For each of the 2,000 firms (indexed by i), realizations of the productivity state $\theta_t^{(i)}$ are drawn at daily frequency

[14] The model could be consistent with either sign of such a relation, depending on whether the cross-firm heterogeneity in P_U is more or less than that of P_L.

[15] The baseline parameter values of HJ are $\gamma = 0.78$, $m = 0.067$, $\delta = 0.044$, $\eta = 0.03$, $\mu = 0.1456$, $\sigma = 0.6114$, $\rho = -0.17$, $F_U = 0.0077$, $F_L = 0.0005$, $P_U = 0.1345$, and $P_L = 1.5626$.

Table 2
Double sorts on flexibility and operating leverage with simulated data

	QFC					
	L	2	3	4	H	H-L
Range(L)	0.77	0.56	0.37	0.24	0.20	–0.57
	(6.20)	(6.22)	(6.22)	(5.40)	(4.96)	(6.07)
	[0.12]	[0.12]	[0.09]	[0.06]	[0.05]	[0.09]
2	0.78	0.58	0.46	0.37	0.26	–0.51
	(6.16)	(6.07)	(6.19)	(6.22)	(5.45)	(5.33)
	[0.13]	[0.11]	[0.09]	[0.07]	[0.06]	[0.09]
3	0.78	0.59	0.50	0.47	0.41	–0.37
	(6.09)	(5.97)	(6.02)	(6.14)	(6.21)	(4.56)
	[0.13]	[0.12]	[0.09]	[0.07]	[0.07]	[0.09]
4	0.78	0.59	0.52	0.51	0.53	–0.25
	(6.02)	(5.97)	(5.97)	(6.15)	(6.30)	(3.37)
	[0.14]	[0.11]	[0.08]	[0.07]	[0.08]	[0.08]
Range(H)	0.73	0.60	0.53	0.55	0.79	0.01
	(5.98)	(5.92)	(5.93)	(6.14)	(6.41)	(0.44)
	[0.13]	[0.11]	[0.08]	[0.07]	[0.09]	[0.08]

This table shows the monthly mean excess returns (in percentage) of 25 portfolios formed by independent sorts on quasi-fixed costs over sales (QFC) and the scale inflexibility measure, Range $=\sigma^{-1}\log(U/L)$, in simulated panels using the model from Section 2. The population consists of firms having disposal value of assets taking on one of the values $P_U = [0.01, 0.06, 0.13, 0.25, 1.00]$ with equal measure. All other parameters are common across firms and are taken from the baseline parameters of HJ. The simulation tabulates results for 200 panels, each consisting of 2000 firms observed for 50 years. The portfolio returns are reported in continuously compounded percentage. Cross-panel means of t-statistics are reported in parentheses. Cross-panel standard deviations of the mean returns are shown in brackets.

and, for each firm, we evaluate its optimal investment/disinvestment decision and hence its endogenous path of assets, $A_t^{(i)}$. From each of these, we compute the daily realizations of each firm's state, $Z_t^{(i)}$, yielding paths of its operating leverage, sales, profitability, stock price, and return moments, $EER(Z_t^{(i)})$ and $VOL(Z_t^{(i)})$.

As a first illustration, we simulate a long history of our cross-section and re-sample each firm's state at monthly intervals. We then sort firm-months into a five-by-five array of portfolios according to their inflexibility, as proxied by the operating range $\sigma^{-1}\log(U^{(i)}/L^{(i)})$, and beginning-of-month operating leverage, as measured by quasi-fixed costs to sales, $m(Z_t^{(i)})^{(1-\gamma)}$. Table 2 presents annualized portfolio returns for the simulation. The simulated returns decrease with operating leverage for the most flexible firms, but the decrease declines with inflexibility. For the most inflexible firms there is no significant difference between the returns of the highest and lowest quintile of operating leverage. These results illustrate the model's implication that flexibility is a primary determinant of the sensitivity of stock returns to operating leverage.

This implication is also confirmed by cross-sectional regressions of monthly excess stock returns on observable firm characteristics in simulated samples. *QFC* is the beginning-of-month ratio of quasi-fixed costs to sales, and *Range*

Table 3
Return regression with simulated data

Variables	(1)	(2)	(3)	(4)
QFC	−0.19		−0.96**	−0.78**
	(1.18)		(2.56)	(2.51)
	[0.23]		[0.31]	[0.28]
Range		0.21**	−0.22**	−0.19*
		(2.22)	(2.06)	(1.95)
		[0.07]	[0.11]	[0.10]
INTER			1.14**	0.91**
			(2.57)	(2.52)
			[0.30]	[0.26]
Beta				0.12**
				(1.98)
				[0.05]

This table shows the results of Fama and MacBeth (1973) regressions of realized monthly excess stock returns on firm characteristics in 200 simulated panels of 2000 firms for 50 years. The population consists of firms having the baseline parameter values of Hackbarth and Johnson (2015) with the disposal value of firm assets taking on the values $P_U = [0.01, 0.06, 0.13, 0.25, 0.50, 1.00]$. *QFC* is the beginning-of-month ratio of quasi-fixed costs to sales; Range is the standardized range of scaled productivity, Z, for each firm. These variables are expressed as percentile rank in each cross-section. The interaction variable, INTER is the product of the ranks. *Beta* is the market-model regression coefficient computed in rolling 60-month lagged windows. The coefficients and t-statistics in parentheses are the cross-panel means of the Fama-MacBeth estimators. The numbers in brackets are the cross-panel standard deviations of the point estimates. The coefficients and the cross-panel standard deviations in the brackets are multiplied by 100 in the reported numbers. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

is the standardized range of the state variable Z for each firm. These variables are expressed in percentile rank in each cross-section. The interaction variable, *Interaction*, is the product of the ranked variables. Table 3 shows the average regression results for 200 simulated panels of 2,000 firms across 50 years.

Columns (1) to (4) in Table 3 show the regression coefficients for four different specifications. As seen in Columns (3) and (4), the coefficients on the interaction term are positive and statistically significant. Moreover, the magnitude is nontrivial economically, as a coefficient of 0.0100 corresponds to 100 basis points of monthly excess return. Because the interaction variable is a product of percentile ranks, the predicted spread between the expected return of the highest and lowest firm ranked by operating leverage is approximately 100 basis points more positive for the least flexible firms than it is for the most flexible firms.

In this panel, there is no unconditional effect of quasi-fixed operating costs (from Column (1)). Although there is a positive unconditional effect of inflexibility on expected returns (from Column (2)), this effect is economically small and switches sign when interacting the two variables. Finally, Column (4) shows that including a standard market risk measure (beta) does not affect the statistical significance of the interaction coefficient. Here beta is the realized market-model regression coefficient computed in rolling 60-month lagged windows (the market return is the equally weighted average of all the firm returns) within each simulated panel. The estimated betas are imperfect measures of true systematic risk due to rapidly changing true exposure. This is a common finding in the investment-based asset pricing literature.

To summarize, building on the results of HJ, this section has shown how and why different degrees of flexibility affect firms' risk/reward properties. The general lesson is that real options contribute a downward-sloping component to expected return (and risk) plotted against operating leverage, whereas assets-in-place contribute an upward-sloping one. Lower adjustment costs (i.e., higher flexibility) increase the influence of the former, and thus decrease the average slope. Using numerical simulations in plausibly parameterized panels of firms with ex ante differing flexibility, we have shown that this relation can be economically large. In extended simulation results, available upon request, we show that the interaction effect studied here is quantitatively robust to the incorporation of more general heterogeneity in firm parameters.

2. Data and Measures

This section describes the construction of measures for firm inflexibility and operating leverage, the two quantities required to test our model's predictions. The measures are grounded in the theory developed above and are straightforward to construct using Compustat Quarterly Industrial Files (Compustat).[16]

We also verify in simulations that they perform reasonably well in small samples at tracking the true unobservable characteristics that we claim they estimate.

2.1 Inflexibility measure

Following the logic described in the previous section, our measure of a firm's inflexibility is a proxy for the width of its inaction region. Intuitively, a firm with less flexible operations (higher adjustment costs) will wait longer before altering its scale to adjust to changes in profitability.

The standardized firm-level range measure, *INFLEX*, is defined as the firm's historical range of operating costs over sales scaled by the volatility of the logarithm of changes in sales over assets. Specifically, the computation for firm i in year t is as follows:

$$INFLEX_{i,t} = \frac{\max_{i,0,t}\left(\frac{OPC}{Sales}\right) - \min_{i,0,t}\left(\frac{OPC}{Sales}\right)}{\mathrm{std}_{i,0,t}\left(\Delta\log\left(\frac{Sales}{Assets}\right)\right)}. \tag{7}$$

Here $\max_{i,0,t}(\frac{OPC}{Sales}) - \min_{i,0,t}(\frac{OPC}{Sales})$ is the range of firm's operating cost (Compustat item XSGAQ + COGSQ) over sales (Compustat item SALEQ) over the period of year 0 to year t, and $\mathrm{std}_{i,0,t}(\Delta\log(\frac{Sales}{Assets}))$ is the standard deviation of the quarterly growth rate of sales over total assets (Compustat

[16] We also construct the measures using Compustat annual data and report these results in the appendix.

item ATQ) over the period of year 0 to year t. Year 0 is firm's beginning year in Compustat. Although in the model inflexibility is a fixed firm characteristic, the empirical measure for a given firm is time-varying because we use only data prior to the observation date.[17]

The range of cost over sales is equivalent to the range of profits over sales, and, under the model, is monotonically related to the width of the inaction region of the state variable Z. The model implies that this range will also scale with the volatility, σ, of the firm's productivity shocks. Firms in more volatile businesses will optimally wait longer to exercise their adjustment options. Because this effect is not related to their inherent flexibility, our measure scales by an estimate of fundamental firm risk. The ratio of sales to total assets is a basic estimate of productivity. In the model, $\Delta\log(\frac{Sales}{Assets})$ is proportional to $\Delta\log(Z)$, whose volatility is σ. In results available upon request, we estimate σ instead using the residuals from the three-stage procedure of Olley and Pakes (1996) to fit each firm's production function. This is substantially more involved econometrically and produces similar results in the tests. For ease of reproducibility, therefore, we use the simpler scaling in the definition of *INFLEX*.

In robustness checks, we also construct an industry-level inflexibility measure defined in the same way as *INFLEX*, but using industry aggregate operating statistics. That is, we compute industry cost, sales, and assets by summing over all quarterly firm observations in each of the 48 Fama and French (1997) industries, and then construct the historical range of industry aggregate operating costs over sales, scaled by the volatility of the growth rate of sales over assets. To the extent that scale flexibility is an industry-specific characteristic, this measure will be less noisy than its firm-specific counterpart.

A second robustness check utilizes the industry-level inflexibility estimates to construct another firm-level flexibility measure.[18] We first construct an inflexibility factor as the return spread between an inflexible-industry portfolio and a flexible-industry portfolio. Specifically, industries are sorted into three groups (bottom 30%, middle 40%, and top 30%) based on the ranked values of the inflexibility measure. Industries with the lowest 30% and highest 30% inflexibility measure form the flexible-industry portfolio and inflexible-industry portfolio, respectively. We then construct firms' loadings on the inflexibility factor as the regression coefficient of firms' monthly returns on the inflexibility factor and use firms' factor loadings as an alternative inflexibility measure.

2.1.1 Validity. Our proxy is new to the literature, and, although easy to compute and grounded in theory, it is also undoubtedly noisy. In practice, many things other than adjustment costs will determine a firm's historical range. Therefore, it is important to ask whether any evidence suggests that it is actually

[17] Results using the full-sample range for each firm are similar and are omitted for brevity.

[18] We thank the editor for suggesting this idea.

Table 4
Validation tests

Variables	Correlation	p-value	N
Inflexible employment	0.36***	≺.0001	3,865
Labor force unionization (*Cov*)	0.14**	.0497	3,457
Labor force unionization (*Mem*)	0.13**	.0500	3,457
Wage premium	0.32***	.0069	1,895
Resal Index	−0.11**	.0140	266
Capital reallocation	−0.24***	≺.0001	153,611
Capital reallocation rate	−0.18***	≺.0001	153,552
Redeployability index	−0.07**	.0309	202,774

This table reports the correlation coefficients between the inflexibility measure, *INFLEX*, and a list of variables that are related to adjustment costs in capital and labor. Inflexibility is constructed as firm's historical range of operating costs over sales scaled by the volatility of the difference between the logarithm of sales over total assets and its lagged value. *Inflexible employment* is an industry-level measure defined by Syverson (2004) as the ratio of the cost for nonproduction workers to the cost of all employees from 1958 to 2009. *Labor force unionization* is an industry-level measure defined as the percentage of employed workers in a firm's primary Census Industry Classification (CIC) industry covered by unions from 1983 to 2005. *Mem* and *Cov* indicate that the variable is constructed from Union Membership and Coverage Database, respectively. *Wage premium* is an industry-level measure defined by Kim (2016) as an estimated fix wage premium paid by each of the 60 U.S. industries (Census Industry Classification (CIC) industry) from 1968 to 2014. *Resal index* is the industry-level capital resalability index defined in Balasubramanian and Sivadasan (2009) for 1987 and 1992. *Capital reallocation* and *Capital reallocation rate* are the firm-level capital reallocation measures defined in Eisfeldt and Rampini (2006) as the sum of acquisitions and sales of property, plant, and equipment or the sum scaled by total assets from 1980 to 2013. *Redeoloyability index* is a firm-level variable defined by Kim and Kung (2017) as the value-weighted average of industry-level redeployability indices across business segments in which the firm operates from 1985 to 2015. All variables are transformed into percentile ranks to limit the impact of outliers. For firm-level variables, we compute the correlation between the firm-level inflexibility measure and the firm-level variable. For industry-level variables, we first compute the industry mean of the inflexibility measure and then calculate the correlation between the industry mean and the industry-level variable. The correlation is computed as follows: we first regress the inflexibility measure (percentile ranks) on each of the listed variables (percentile ranks) and then transform the regression coefficient to the correlation by multiplying by the ratio of the standard deviations of independent and dependent variables. Standard errors are clustered by industry in the regression. p-values from the regressions are reported. N is the number of observations in each estimation. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

picking up variation in firm flexibility and whether it is doing so as well as, or better than, alternatives available in the literature.

As an initial gauge of the validity of our measure, we examine the relation between *INFLEX* and a list of variables each of which have been used by empiricists to capture aspects of adjustment costs for capital or labor. Each of these can be compared with our measure for some subset of the firm-year observations in our sample. Table 4 reports the correlation coefficients between the inflexibility measure and those variables.[19]

[19] For firm-level variables, we compute the correlation between our firm-level inflexibility measure and the firm-level variable. For industry-level variables, we first compute the industry mean of our inflexibility measure and then calculate the correlation between the industry mean and the industry-level variable. All variables are transformed into percentile ranks to limit the impact of outliers. The table reports p-values for the coefficient from a regression of *INFLEX* on each of the listed alternatives. Standard errors are clustered by industry. Clustering standard errors by year or by industry and year delivers quite similar and sometimes stronger significance levels. For comparability across measures, the regression coefficients are transformed into equivalent correlation estimates by multiplying by the ratio of the standard deviations of independent and dependent variables.

The top four rows examine measures from the labor literature. First, we consider an *Inflexible employment* index in the spirit of Syverson (2004) that we compute as the ratio of the cost for nonproduction workers to the cost of all employees.[20] As nonproduction workers are generally regarded as skilled workers and production workers as unskilled or semi-skilled workers, Belo et al. (forthcoming) argue that it is easier and less costly for firms to hire or fire production workers compared with nonproduction workers. As such, we anticipate a positive relation between the *Inflexible employment* index and our inflexibility measure. Next, we use *Labor force unionization* variables constructed from Union Membership and Coverage Database, coverage *Cov* and membership *Mem* (see, e.g., Hirsch and MacPherson 2002). For example, Connolly, Hirsch, and Hirschey (1986) and Chen, Kacperczyk, and Ortiz-Molina (2011) also use coverage, which is defined as the percentage of employed workers in a firm's primary Census Industry Classification (CIC) industry covered by unions. Because labor unions decrease firms' operating flexibility, we should expect a positive relation between union coverage rate and our inflexibility measure. The empirical labor literature has also related labor adjustment costs to persistent inter-industry wage differentials (see, e.g., Hamermesh 1993; Dube, Freeman, and Reich 2010). Higher wage rates (for equivalent jobs) are associated with less flexible employment. The fourth row considers *Wage premium* across 60 U.S. industries, as estimated by Kim (2016). As with other labor variables, our interpretation implies that this statistic should be positively correlated with *INFLEX*.

As Table 4 shows, the correlation coefficients of all four labor adjustment cost variables with *INFLEX* are indeed positive. Each of the correlations is also highly statistically significant.

Next, we examine asset reallocation and redeployment variables. Balasubramanian and Sivadasan (2009) create an index of capital resalability, *Resal Index*, which is the share of used capital investment in total capital investment at the four-digit SIC aggregate level. Given that it measures capital flexibility, it should be negatively related to our range measure of inflexibility, which is confirmed by the table. Furthermore, we examine the capital reallocation measures proposed by Eisfeldt and Rampini (2006) and defined as the sum of acquisitions and sales of property, plant, and equipment (*Capital reallocation*) or the sum scaled by assets (*Capital reallocation rate*). Intuitively, firms with higher capital reallocation should be more flexible; hence, we should expect a negative relation between capital reallocation and our inflexibility measure, which is indeed revealed by Table 4. Lastly, we consider Kim and Kung's (2017) asset redeployability measure (*Redeployability index*), which is constructed as the value-weighted average of industry-level

[20] The cost for nonproduction workers and the cost for all employees are from the U.S. Census Bureau's economic census data from 1958 to 2009 for industries with SIC codes from 2011 to 3999. Variables in that database include "payment for production workers" and "payment for all employees".

redeployability indices across business segments in which the firm operates over the period of 1985–2015. The industry-level redeployability index is constructed as the weighted average of 180 asset category's redeployability score (i.e., the ratio of the number of industries that use a given asset to the number of total industries in the BEA table) for each of the 123 BEA industries. Intuitively, firms with higher asset redeployability should be more flexible; therefore, we predict a negative relation between redeployability and inflexibility.

Table 4 again confirms these predictions. Each of the capital flexibility measures is negatively correlated with *INFLEX*. The magnitudes of the numbers are smaller than those for the labor variables, but even the smallest (which can be computed only for a small sample) is still statistically significant. Overall, the table provides reassuring support for our assertion that *INFLEX* contains important information about firms' scale adjustment flexibility.

To further test the validity of our measure, we assess its performance relative to criteria used in the empirical corporate finance literature.[21] Specifically, this literature seeks to identify inflexibility via firms' response to investment opportunities. Following Jovanovic and Rousseau (2014), we run standard panel investment regressions and include as an independent variable the interaction of Tobin's q with alternative proposed measures of flexibility. Jovanovic and Rousseau (2014) argue that young firms are more flexible, and they therefore interact q with a dummy variable for whether a firm is less than 3 years old. They explicitly cite the positive estimated interaction coefficient as validating their interpretation of age as capturing flexibility.

Following the same logic, we construct dummy variables for both our range measure and other measures proposed in the literature. We then use these in a variety of alternative regressions, employing different measures of q, different fixed effects, and different estimation methodologies. For comparability across measures, our dummies are constructed to identify flexible firms.[22] We merge all variables (all independent and dependent variables) together and obtain a sample of 36,378 firm-year observations over the period of 1985–2005.[23] More specifically, we run regressions of investment on various measures of q, an interaction term of q and a dummy variable for flexibility, lagged investment and lagged cash flow.[24] Table 5 presents the results.

[21] We thank the referee for suggesting this idea.

[22] The dummy variable for *INFLEX*, *Inflexible Employment*, *Unionization*, *Wage Premium*, or *Firm Age* is equal to 1 if the variable is below the median of its distribution every year. The dummy variable for *Resal Index*, *Capital Reallocation*, or *Redeployability Index* is equal to 1 if the variable is above the median of its distribution every year.

[23] The unionization data end at 2005, and the redeployability index starts from 1985.

[24] Investment is defined as capital expenditure (Compustat item CAPX), scaled by lagged total assets (Compustat item AT). Cash flow is defined as the sum of income before extraordinary items (Compustat item IB) and depreciation and amortization (Compustat item DP), scaled by lagged total assets. Tobin's q (firm-level q) is

Table 5
Investment flexibility test: Interactions with q

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	INFLEX	Redeployability index	Wage premium	Inflexible employment	Unionization (Cov)	Resal index	Kallocation	Firm Age
A. Firm-level q								
				OLS estimation				
q	0.33	0.59	0.35	0.29	0.86	0.41	0.42	0.56
	(2.41)	(3.62)	(2.98)	(1.81)	(4.94)	(3.28)	(3.35)	(3.96)
INTER	0.43***	−0.25	0.21	0.51***	−0.59	0.08	0.11	0.16
	(4.35)	(2.44)	(1.37)	(2.98)	(4.47)	(0.67)	(1.16)	(1.30)
				Arellano-Bond dynamic panel-data estimation				
q	1.47	1.80	1.59	1.56	1.49	1.48	1.91	0.68
	(12.83)	(12.93)	(13.57)	(13.04)	(9.82)	(10.53)	(17.32)	(6.32)
INTER	0.66***	−0.28	0.11	0.29	0.24	0.33*	−0.85	0.46***
	(3.55)	(1.63)	(1.06)	(1.45)	(1.45)	(1.69)	(0.67)	(3.43)
B. Alternative q								
				OLS estimation: Industry-level q				
INTER	0.38***	−0.28	0.12	0.32***	−0.46	0.04	0.10	0.07
	(4.93)	(3.22)	(1.01)	(2.82)	(4.65)	(0.37)	(1.47)	(0.73)
				OLS estimation: Aggregate market's q				
INTER	0.38***	−0.27	−0.03	0.50***	−0.61	−0.13	0.17**	0.01
	(4.21)	(4.49)	(0.28)	(3.62)	(0.90)	(1.34)	(2.51)	(0.67)
				OLS estimation: Bond market's q				
INTER	0.98***	−0.63	−0.23	1.22***	−1.27	−0.37	0.45***	0.09
	(4.98)	(4.47)	(0.84)	(4.64)	(5.58)	(1.52)	(3.30)	(0.41)
				Arellano-Bond dynamic panel-data estimation: Industry-level q				
INTER	0.59***	−0.27	0.01	−0.05	0.14	−0.13	−0.38	0.71***
	(3.76)	(1.84)	(0.09)	(0.30)	(0.96)	(0.77)	(3.51)	(6.03)
				Arellano-Bond dynamic panel-data estimation: aggregate market's q				
INTER	0.79***	0.53**	−0.09	−1.36	0.32	−1.31	−0.77	0.85***
	(3.12)	(2.12)	(0.87)	(3.62)	(1.53)	(2.51)	(5.80)	(4.58)
				Arellano-Bond dynamic panel-data estimation: bond market's q				
INTER	2.92***	1.00*	−0.26	−3.51	0.82*	−2.56	−1.77	1.86***
	(5.10)	(1.71)	(0.99)	(3.95)	(1.75)	(1.99)	(5.85)	(4.55)
C. With fixed effects (firm-level q)								
				With firm fixed effects				
INTER	0.76***	−0.11	0.29	0.29	−0.16	−0.06	−0.27	0.69***
	(5.10)	(0.86)	(1.57)	(1.05)	(0.71)	(0.36)	(2.74)	(4.15)
				With industry fixed effects				
INTER	0.39***	−0.04	0.19	0.17	−0.15	−0.12	0.05	0.11
	(4.02)	(0.46)	(1.07)	(0.80)	(1.10)	(0.94)	(0.53)	(0.92)

This table shows results from regressions of investment on various measures of q, an interaction term of q and a dummy variable for flexibility (*INTER*), lagged investment, and lagged cash flow. Investment is defined as capital expenditure (Compustat item CAPX), scaled by lagged total assets (Compustat item AT). Cash flow is defined as the sum of income before extraordinary items (Compustat item IB) and depreciation and amortization (Compustat item DP), scaled by lagged total assets. Tobin's q (firm-level q) is defined as the sum of market value of equity (Compustat item CSHO$\times$PRCC) and total assets minus the sum of book value of equity (Compustat item CEQ) and deferred taxes (Compustat item TXDB), scaled by lagged total assets. Industry-level q is constructed using the same formula with variables aggregated by industry, where industries are classified by four-digit SIC codes. Flexibility is proxied by the list of variables we study in the validation tests. Details about these variables are in the caption to Table 4. Firm age is defined as the number of years a firm exists in Compustat annual file. The dummy variable for *INFLEX*, *Inflexible employment*, *Unionization*, *Wage premium*, and *Firm age* is equal to 1 if the variable is below the median of its distribution every year. The dummy variable for *Resal index*, *Capital reallocation*, and *Redeoloyability index* is equal to 1 if the variable is above the median of its distribution every year. Four different measures of q are firm-level q, industry-level q, which are constructed with Compustat annual data, aggregate market's q and bond market's q, which are constructed in Philippon (2009) over 1953–2007. For industry-level variables, we assign the industry-level value to all firms in that industry every year. We merge all variables (all independent and dependent variables) together and use one sample for each test in this table. We require investment to be nonnegative in the regressions. The unionization data ends at 2005 and the Redeployability index starts from 1985. Finally, we obtain a sample of 36,378 firm-year observations over the period of 1985–2005. Panel A reports the estimation coefficients on firm-level q and the interaction term, using both OLS estimation and the Arellano-Bond dynamic panel-data estimation methods. Panel B reports the estimation coefficients on the interaction term for three alternative measures of q. Panel C reports the estimation coefficients when firm fixed effects or industry fixed effects are employed in the OLS estimation. Standard errors are clustered at year in the OLS estimation. The coefficients are multiplied by 100. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively. We only indicate the significance level for positive coefficients on *INTER*.

Panel A reports the coefficients on firm-level q and the interaction term, using both OLS estimation and the dynamic panel-data estimation of Arellano and Bond (1991). For brevity, the remainder of the table just shows the interaction coefficient. Panel B reports the estimated coefficients for three alternative measures of q: industry-level q, aggregate market's q, and bond market's q as constructed by Philippon (2009). Finally, panel C reports the estimated coefficients when firm fixed effects or industry fixed effects are employed in the OLS estimation.

The results show that the coefficient on the interaction term (*INTER*) for our inflexibility measure is positive and significant in every specification, and its positive performance is the most consistent of any of the measures considered. The strength of the interaction effect as picked up by the age measure is matched only in some specifications by firm age.[25] The findings here not only constitute a successful validation of our measure; they also demonstrate that it represents a valuable contribution to the empirical literature on firm investment behavior.

To further extend the ideas of the preceding test, we next follow Kim and Kung (2017) and interact our inflexibility proxy with volatility measures in investment regressions. Kim and Kung's interpretation is that inflexible firms delay investment more in response to increased uncertainty. Although the sensitivity of investment to volatility is a less familiar idea than that of q, their interpretation and tests are consistent with the predictions of real options theory. In Table 6, we follow their test design and regress investment on the *VIX* index from Chicago Board Options Exchange (CBOE), an interaction term of VIX with a dummy variable for flexibility (*INTER*), lagged q, lagged investment, and lagged cash flow. For comparison, the test also shows the performance of Kim and Kung's redeployability index.[26] We merge all variables together and obtain a sample of 98,892 firm-year observations over the period of 1991–2007.[27]

The main specification uses the average *VIX* index in the last quarter in year t-1 in the regression for year t. An alternative definition (*VIX2*) is defined as the value of *VIX* on the last day in year t-1. The dummy variable for *INFLEX* is equal to 1 if the variable is below the median of its distribution every year.

defined as the sum of market value of equity (Compustat item CSHO×PRCC) and total assets minus the sum of book value of equity (Compustat item CEQ) and deferred taxes (Compustat item TXDB), scaled by lagged total assets. Industry-level q is constructed using the same formula with variables aggregated by industry, where industries are classified by four-digit SIC codes.

25 The comparison with Jovanovic and Rousseau's (2014) age proxy raises the question of whether our range measure is mechanically picking up older firms. In fact, the correlation across firm-years of *INFLEX* with firm age is an insignificant 0.011.

26 The specification departs in one respect from Kim and Kung's in that we employ annual investment data, rather than quarterly because both our inflexibility measure and their redeployability index are in annual frequency. Also, the main analysis in Kim and Kung (2017) uses the events of the First Gulf War and the September 2011 terrorist attacks as shocks to aggregate economic uncertainty. The event study within a short time window poses a high frequency data requirement in the main analysis in Kim and Kung (2017). However, our test does not involve any event and thus quarterly data are not a necessary choice. The sample period for our test and their test is slightly different: 1989–2009 in Kim and Kung (2017) and 1991–2007 in our test.

27 The VIX index starts from 1990, and the q variables from Philippon (2009) end at 2007.

Table 6
Investment flexibility test: Interactions with volatility

	VIX	INTER	Lagged q	Lagged investment	Lagged cash flow
A. Firm-level q					
INFLEX	−0.06**	0.01*	1.60***	16.13***	0.01*
	(2.24)	(1.92)	(9.61)	(8.69)	(1.95)
Redeployability index	−0.06**	0.01	1.62***	16.17***	0.01**
	(2.03)	(1.36)	(9.64)	(8.72)	(1.98)
B. Industry-level q					
INFLEX	−0.06**	0.02***	1.61***	20.19***	0.002
	(2.44)	(3.46)	(10.85)	(11.76)	(1.49)
Redeployability index	−0.06**	0.01	1.61***	20.29***	0.002
	(2.03)	(1.44)	(10.84)	(11.81)	(1.52)
C. Aggregate market's q					
INFLEX	−0.09***	0.03***	0.01	21.35***	0.003
	(3.03)	(4.01)	(0.44)	(13.22)	(1.50)
Redeployability index	−0.08***	0.01*	0.02	21.49***	0.003*
	(2.60)	(1.74)	(0.04)	(13.29)	(1.73)
D. Bond market's q					
INFLEX	−0.08***	0.02***	8.69***	20.30***	0.002
	(3.66)	(4.19)	(4.48)	(12.44)	(1.39)
Redeployability index	−0.08***	0.02**	8.79***	20.43***	0.002
	(3.56)	(2.40)	(4.54)	(12.55)	(1.43)
E. Firm-level q and an alternative definition of VIX (VIX2)					
INFLEX	−0.06**	0.01**	1.63***	16.11***	0.01**
	(2.29)	(2.00)	(9.58)	(8.72)	(2.00)
Redeployability index	−0.06**	0.005	1.63***	16.14***	0.01**
	(1.97)	(1.13)	(9.62)	(8.74)	(2.03)

The table shows results from regressions of investment on the VIX index, an interaction term of the VIX index and a dummy variable for flexibility (*INTER*), lagged q, lagged investment, and lagged cash flow. Investment is defined as capital expenditure (Compustat item CAPX), scaled by lagged total assets (Compustat item AT). Cash flow is defined as the sum of income before extraordinary items (Compustat item IB) and depreciation and amortization (Compustat item DP), scaled by lagged total assets. Tobin's q (firm-level q) is defined as the sum of market value of equity (Compustat item CSHO$\times$PRCC) and total assets minus the sum of book value of equity (Compustat item CEQ) and deferred taxes (Compustat item TXDB), scaled by lagged total assets. Industry-level q is constructed using the same formula with variables aggregated by industry, where industries are classified by four-digit SIC codes. VIX index is the implied volatility of the S&P 500 index from the Chicago Board Options Exchange. The average VIX index in the last quarter in year t-1 is used in the regression for year t. An alternative definition of VIX ($VIX2$) is defined as the VIX index on the last day in year t-1. Inflexibility (*INFLEX*) is measured by firm's historical range of operating costs over sales scaled by the volatility of the difference between the logarithm of sales over total assets and its lagged value. *Redeoloyability index* is the firm-level redeployability index constructed in Kim and Kung (2017) as the value-weighted average of industry-level redeployability indices across business segments in which the firm operates over 1985–2015. The dummy variable for *INFLEX* is equal to 1 if the variable is below the median of its distribution every year. The dummy variable for *Redeployability index* is equal to 1 if the variable is above the median of its distribution every year. Four different measures of q are firm-level q, industry-level q, which are constructed with Compustat annual data, aggregate market's q and bond market's q, which are constructed in Philippon (2009) over 1953–2007. We merge all variables (all independent and dependent variables) together and use one sample for each test in this table. We require investment to be nonnegative in the regression. The VIX index starts from 1990 and the q variables from Philippon (2009) ends at 2007. Finally, we obtain a sample of 98,892 firm-year observations over the period of 1991–2007. Panels A, B, C, and D report the estimation coefficients when each of the four different q is used in the regression. Panel E reports the estimation results when firm-level q and the alternative definition of VIX (*VIX2*) are employed. Firm fixed effects are employed in all regressions and the standard errors are clustered at year. The coefficients are multiplied by 100. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

The dummy variable for *Redeployability Index* is equal to 1 if the variable is above the median of its distribution every year. Again, we employ four different measures of q for robustness. Panels A, B, C, and D in Table 6 report the estimation coefficients when each of the four different q is used in the regression. Panel E reports the estimation results when firm-level q and the alternative definition of *VIX* (*VIX2*) are employed.

Once again, the coefficient on the interaction term (*INTER*) for our inflexibility measure is of the predicted (positive) sign, and is highly significant. Moreover, in this setting, the measure outperforms the *Redeployability Index* in magnitude and statistical significance.[28] Again, the range measure succeeds in capturing an important feature of firm investment.

To summarize, the correlations in Table 4 first establish that our range-based measure shares common information with numerous other proxies suggested in the empirical literature for factor adjustment costs. The investment regressions results in Tables 5 and 6 then provide explicit evidence that real firm decisions are associated with the range measure in precisely the manner that would be expected under the interpretation (suggested by the model) that range is associated with adjustment costs. The range is therefore a valid measure of inflexibility and also a valuable contribution to the empirical investment literature in its own right. It is worth emphasizing that the investment tests verified falsifiable ex ante implications of the model, in a setting unrelated to the asset pricing tests in which the measure will be used in Section 4.

2.2 Operating leverage measure

The model's main implication is an interaction of firm flexibility with operating leverage. As discussed in Section 2, our preferred measure of operating leverage is the ratio of quasi-fixed production costs to sales. In the model, these two quantities are mA and $\theta^{1-\gamma}A^{\gamma}$, and their ratio, $mZ^{1-\gamma}$, monotonically increases with the firm-specific state variable Z, which is not directly observable. However, we can plausibly estimate the numerator and denominator of this ratio. *QFC* denotes the resultant measure. Our strategy employs a standard time-series regression methodology using quarterly Compustat data to estimate quasi-fixed costs for each firm-year.

Intuitively, quasi-fixed costs are those that do not scale with contemporaneous sales. Therefore, our regressions aim to estimate next-period's expected costs *even if sales were zero.* To do this, we run 5-year rolling-window regressions of operating costs on its first lag, contemporaneous sales, and lagged sales. The predicted fixed costs next period is the regression intercept plus the

[28] The relatively weaker performance of Kim and Kung's measure in these regressions may be due to the use of annual rather than quarterly data.

contribution of the lagged variables. The baseline measure of *QFC* in the year following the 5-year window equals this value, scaled by sales.[29]

Specifically, the regression specification is as follows:

$$Cost_{i,q} = a_i + b_i Cost_{i,q-1} + c_i Sales_{i,q} + d_i Sales_{i,q-1} + \epsilon_{i,q}, \tag{8}$$

where $Cost_{i,q}$ and $Cost_{i,q-1}$ are the operating costs of firm i in quarter q and q-1, respectively. $Sales_{i,q}$ and $Sales_{i,q-1}$ are sales value of firm i in quarter q and q-1, respectively. Then, *QFC* for firm i in year t is:

$$QFC_{i,t} = \frac{a_i + b_i Costmean_{i,t-1} + d_i Salesmean_{i,t-1}}{Salesmean_{i,t-1}}. \tag{9}$$

Here, $Costmean_{i,t-1}$ and $Salesmean_{i,t-1}$ are average costs and average sales over four quarters in year t-1. To understand these estimates, a typical value for a given firm-year might be 0.17, meaning that, as of the end of the prior year, we would expect the firm to have unavoidable costs equal to 17% of this year's sales.

We also construct an alternative measure of *QFC* as the regression intercept scaled by sales over assets from 5-year rolling-window regressions of operating costs over assets on sales over assets. The regression specification is as follows:

$$Cost_{i,q}/Assets_{i,q} = a_i + b_i Sales_{i,q}/Assets_{i,q} + \epsilon_{i,q}, \tag{10}$$

This measure of *QFC* for firm i in year t is a_i, scaled by the average sales-over-assets ratio over four quarters in year t-1. As robustness test, we reduce the noisiness of *QFC* measures by increasing the minimum number of observations from 10 to 15 for every 5-year window.

2.3 Performance of empirical measures in a simulated sample

We have grounded our estimation strategy firmly in theory, but one may ask how well our estimators should be expected to perform, even within the model. Does the model imply that, in finite samples, they will do a good job at capturing the theoretical quantities they are supposed to represent?

We address this by a simulation experiment in which we use the simulated values of firms' accounting numbers (sales, assets, and costs) to reproduce exactly the empirical procedures described above. Specifically, we simulate 200 panels of 2,000 firms for 50 years, and then construct our empirical measures in each cross-section.[30] We can then compare these to the true population quantities. Table 7 shows the results.

[29] To minimize the impact of outliers and data errors, we require that the rolling windows for each regression contain at least 10 observations and quarterly growth rates of assets, costs, and sales are no more than plus or minus 75%. The data filters lower the number of firm-months in which *QFC* estimates can be produced by about 3%. Our test results below are robust to alternative filtering procedures.

[30] The simulation design is identical to the one described in Section 1.3. The same cross-section of firm parameters is employed.

Table 7
Performance of empirical proxies in simulated panels

A. Inflexibility

	$T=10$	$T=25$	$T=50$
$corr(\log(U/L)/\sigma, INFLEX)$	0.3188 (0.0269)	0.4046 (0.0237)	0.5567 (0.0378)

B. Operating leverage

	$q=1$	$q=2$	$q=4$
$corr(mZ^{(1-\gamma)}, QFC)$	0.6445 (0.0599)	0.6307 (0.0624)	0.6143 (0.0687)

This table shows correlations between our empirical measures and their population counterparts in simulated samples of 2000 firms as described in the caption to Table 2. Observations of each firm's assets, sales, and costs are tabulated at quarterly frequency within each simulated path, and the empirical estimators are constructed from these. The numbers reported are cross-firm correlations of the rank of each statistic with the true firm characteristic. The cross-panel standard deviations are given in parentheses. Panel A considers the estimator of firm inflexibility as summarized by the standardized range $\log(U/L)/\sigma$. *INFLEX* estimates this by the realized range of each firm's costs-to-sales ratio divided by the realized standard deviation of the log changes in the sales-to-asset ratio. The performance of the estimator is shown as a function of the length of the observation history, T, in years. Panel B considers the estimator of operating leverage as summarized by the ratio of quasi-fixed costs to sales, whose true value is $mZ^{(1-\gamma)}$. The estimator *QFC* is constructed from a regression estimate of fixed costs in a 5-year window of quarterly observations and divided by sales observed at the end of that window (see Equations (8) and (9)). The performance of the estimator is shown as a function of the quarter after estimation, q, when the true statistic is computed.

The table reports the cross-firm correlations of each statistic with the true firm characteristic. Both variables are expressed as percentile ranks within the cross-section. Panel A compares the *INFLEX* estimates to the true standardized ranges, $\sigma^{-1}\log(U/L)$, which differ across firms because of the heterogeneity in adjustment cost parameters. In small samples, not all firms will have fully traversed their inaction regions. So we expect the estimator to do increasingly well as the length of the observation history increases. The table shows the performance of *INFLEX* as a function of the sample length, T, in years. The results reveal that, even for a 10-year panel, the expected correlation is quite positive (on the order of 30%) and highly significant.

Panel B considers the estimator of operating leverage, *QFC*, constructed from rolling-window regressions within the simulated histories exactly as per Equations (8) and (9). These are compared to the true value $mZ^{(1-\gamma)}$, which differs across firms because of the heterogeneity in the realizations of the firm-specific stochastic process $Z=Z_{i,t}$. In the empirical work, we run our estimation annually, and then fix the estimates throughout the following year. (The tests use monthly stock returns.) To see whether the performance of the estimator declines significantly as it becomes more out-of-date, the table reports correlations as a function of the quarter after estimation, q, when the true statistic is recorded. That is, q represents the estimation lag. The results show that *QFC* works well with a one-quarter lag (with a correlation over 60%) and that this performance suffers very little decline even a year after estimation.

In sum, we have introduced here the two empirical proxies that form the basis of our empirical work. They are straightforward to construct and have natural interpretations in the context of the model. We have provided supporting evidence, via simulation and via comparison with other proxies suggested by the literature, that they capture the intended information. We now examine the model's implications regarding their relation with stock returns.

3. Empirical Results

Using our measures of scale inflexibility and operating leverage, this section tests the model's primary implication that the relation of stock returns to operating leverage depends on adjustment frictions. Our hypothesis is that the strength of the relation increases with inflexibility, that is, operating leverage increases expected returns *more* for more inflexible firms.[31]

3.1 Portfolio sorts

To gauge the economic magnitude of the hypothesized effect, we first study portfolios formed by sorts on the two variables. Specifically, In June of each year t, we assign stocks into quintile portfolios based on firms' inflexibility measure. Independently, firms are sorted into quintile portfolios based on their estimated quasi-fixed costs over sales. Monthly returns on the resultant 25 portfolios are then calculated from July of year t to June of year $t+1$. Table 8 reports summary statistics of the 25 independently sorted portfolios for six different portfolio characteristics: the inflexibility measure, quasi-fixed costs over sales, return on assets, capital expenditure, market value of debt, and market equity.

Panels A and B of Table 8 show the sorting variables *INFLEX* and *QFC*, respectively. Next, panel C contains return on assets, which becomes much worse as quasi-fixed costs increase. This finding makes intuitive sense, as quasi-fixed costs are inversely related to profitability. Panel E suggests that inflexible firms are associated with lower debt levels than flexible firms, perhaps because financial and real flexibility are substitutes (see also D'Acunto et al. forthcoming). That is, negative productivity shocks could lead inflexible firms to financial distress or even bankruptcy if such firms have not retained high financial flexibility (by taking on less debt). Lastly, market equity in panel F exhibits a strong pattern: firm size decreases as quasi-fixed costs increase, for all levels of inflexibility.

Table 9 presents equally weighted average monthly portfolio excess returns and abnormal returns for each of the 25 portfolios over the 1980–2016 period.

[31] Monthly returns from the Center for Research in Security Prices (CRSP) are used for the asset pricing tests. Following Fama and French (1992), only NYSE-, AMEX-, and NASDAQ-listed securities with share codes 10 and 11 are included in the sample. Thus, American depositary receipts, real estate investment trusts, and units of beneficial interest are excluded. Furthermore, to limit the impact of small stocks, we exclude stocks with price less than $1 from the sample. Finally, following the standard practice in the empirical asset pricing literature, financial firms and regulated utilities are excluded.

Table 8
Summary statistics

	QFC					QFC				
	L	2	3	4	H	L	2	3	4	H
	A. Inflexibility					*B. Quasi-fixed costs over sales*				
INFLEX(L)	0.59	0.68	0.72	0.77	0.81	0.03	0.10	0.17	0.27	0.50
2	1.31	1.31	1.32	1.35	1.39	0.04	0.10	0.17	0.29	0.51
3	2.05	2.04	2.04	2.07	2.12	0.04	0.10	0.17	0.29	0.53
4	3.23	3.25	3.26	3.30	3.42	0.04	0.10	0.18	0.30	0.60
INFLEX(H)	11.90	12.39	14.54	15.10	19.70	0.04	0.10	0.18	0.31	1.15
	C. Return on assets					*D. Capital expenditure*				
INFLEX(L)	0.10	0.10	0.10	0.09	0.10	0.06	0.06	0.06	0.06	0.09
2	0.10	0.09	0.09	0.07	0.07	0.06	0.06	0.06	0.06	0.06
3	0.10	0.09	0.08	0.06	0.02	0.06	0.06	0.07	0.06	0.06
4	0.09	0.09	0.08	0.05	–0.01	0.07	0.06	0.06	0.07	0.06
INFLEX(H)	0.09	0.09	0.06	0.04	–0.12	0.07	0.07	0.08	0.07	0.06
	E. Market leverage					*F. Market equity*				
INFLEX(L)	0.24	0.22	0.22	0.23	0.22	2.79	2.33	1.87	2.34	1.01
2	0.24	0.22	0.22	0.21	0.19	2.51	2.45	2.04	1.68	1.49
3	0.23	0.23	0.21	0.19	0.20	5.52	3.51	2.24	1.81	1.15
4	0.21	0.20	0.19	0.18	0.17	4.02	3.20	2.84	1.67	0.86
INFLEX(H)	0.18	0.17	0.17	0.15	0.13	2.51	2.12	2.99	1.95	0.78

This table reports summary statistics of 25 portfolios sorted on a firm-level measure of inflexibility (*INFLEX*) and firm-level quasi-fixed costs over sales (*QFC*), which are constructed using Compustat quarterly data. In June of each year t, NYSE-, AMEX-, and NASDAQ-listed stocks are sorted into quintile portfolios based on the inflexibility measure. Independently, firms are sorted into quintile portfolios based on their estimated quasi-fixed costs over sales. Inflexibility is defined as firm's historical range of operating costs over sales scaled by the volatility of the difference between the logarithm of sales over total assets and its lagged value. Firm-level estimates of *QFC* are obtained by running 5-year (20-quarter) rolling-window regressions of operating costs on its first lag, contemporaneous sales, and lagged sales. The baseline measure of *QFC* in the year following the 5-year estimation period equals the sum of regression intercept and predicted operating costs, scaled by sales. We require firms to have at least ten quarterly observations in the 5-year window. Return on assets is defined as earnings before interests and taxes (Compustat item EBIT) scaled by lagged total assets (Compustat item AT). Capital expenditure is defined as capital expenditure (Compustat item CAPX) scaled by lagged total assets. Market leverage is defined as book value of long-term debt (Compustat item DLTT) divided by the sum of market value of equity and book value of long-term debt. Market value of equity is firm's market capitalization (in millions) constructed using monthly return data from CRSP. Panels A, B, C, D, E, and F show the average inflexibility level, quasi-fixed cost over sales, return on assets, capital expenditure, market leverage, and market equity of the portfolios, respectively. The sample period is from July 1980 to December 2016.

Panels A and B show the portfolio excess returns with the baseline measure and the alternative measure of *QFC*. Panel C reports portfolio excess returns when 20% smallest size firms are excluded from the sample. Panel D shows portfolio abnormal returns (i.e., alpha) by adjusting for the Fama and French (2015) five factors. The results show a significant interaction effect between inflexibility and operating leverage: the excess return spread between the lowest and highest quasi-fixed costs quintile is monotonically increasing from the most flexible firms to the most inflexible firms.

In panel A, there is no significant increase in returns with operating leverage for the most flexible firms. However, for the most inflexible firms the return spread between lowest and highest operating leverage firms is an economically and statistically significant 88 basis points per month. This finding is consistent with the primary implication of the model derived in

Table 9
Portfolio excess returns using firm-level inflexibility measure

	QFC						
	L	2	3	4	H	H-L	*t*–stat
A. Baseline results							
INFLEX(L)	1.09	1.19	1.04	1.10	1.38	0.30	(0.77)
2	1.11	1.10	1.21	1.37	1.43	0.33*	(1.70)
3	1.19	1.20	1.21	1.41	1.59	0.40**	(2.33)
4	1.10	1.20	1.24	1.41	1.76	0.66***	(3.40)
INFLEX(H)	1.05	1.46	1.38	1.38	1.93	0.88***	(3.70)
B. Alternative definition of QFC							
INFLEX(L)	1.16	1.02	1.15	1.22	0.99	−0.16	(0.30)
2	1.14	1.18	1.26	1.22	1.07	−0.07	(0.41)
3	1.15	1.19	1.23	1.30	1.39	0.24	(1.47)
4	1.29	1.36	1.34	1.44	1.58	0.28	(1.60)
INFLEX(H)	1.13	1.18	1.35	1.61	1.75	0.62***	(2.84)
C. Excluding 20% smallest size firms							
INFLEX(L)	1.21	1.24	1.26	1.34	1.49	0.29	(0.69)
2	1.14	1.23	1.38	1.39	1.53	0.39**	(2.24)
3	1.29	1.33	1.14	1.65	1.68	0.39**	(2.51)
4	1.26	1.21	1.36	1.53	1.95	0.69***	(3.55)
INFLEX(H)	1.23	1.42	1.68	1.58	2.14	0.90***	(3.83)
D. Fama and French (2015) five-factor alpha							
INFLEX(L)	0.09	0.21	0.08	0.16	0.50	0.40	(0.83)
2	0.14	0.09	0.25	0.55	0.75	0.61***	(3.08)
3	0.26	0.25	0.26	0.57	0.97	0.71***	(4.32)
4	0.21	0.38	0.39	0.73	1.31	1.11***	(6.93)
INFLEX(H)	0.30	0.86	0.72	0.76	1.55	1.25***	(5.86)

This table reports the monthly excess returns (in percentage) of 25 portfolios sorted on a firm-level measure of inflexibility (*INFLEX*) and firm-level quasi-fixed costs over sales (*QFC*), which are constructed using Compustat quarterly data. Inflexibility is measured by firm's historical range of operating costs over sales scaled by the volatility of the difference between the logarithm of sales over assets and its lagged value. Firm-level estimates of *QFC* are obtained by running 5-year (20-quarter) rolling-window regressions of operating costs on its first lag, contemporaneous sales, and lagged sales. The baseline measure of *QFC* in the year following the 5-year estimation period equals the sum of regression intercept and predicted operating costs, scaled by sales. An alternative definition of *QFC* is constructed as the intercept from a 5-year (20-quarter) rolling-window regression of operating costs over total assets on sales over total assets, scaled by sales over total assets. We require firms to have at least ten quarterly observations for every 5-year window. In June of each year t, NYSE-, AMEX-, and NASDAQ-listed stocks are sorted into quintile portfolios based on the inflexibility measure. Independently, firms are sorted into quintile portfolios based on their estimated quasi-fixed costs over sales. Monthly returns on the resultant 25 portfolios are then calculated from July of year t to June of year $t+1$. Panels A and B report equally weighted portfolio excess returns when we use the baseline definition of *QFC* and the alternative definition of *QFC*, respectively. Panel C reports equally weighted portfolio excess returns when firms in the lowest quintile by size are excluded from the sample. Panel D reports portfolio abnormal returns (i.e., alpha), which are computed by running time-series regression of portfolio excess returns on risk factors in the Fama and French (2015) five-factor model. The sample period is from July 1980 to December 2016. t-statistics for the return spread between the lowest and highest *QFC* quintiles are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Section 2. Indeed, the pattern in Table 9 is strikingly similar to the one found in model simulated data shown in Table 2. The results in panel B are supportive, indicating that the findings are robust to the alternative estimation of quasi-fixed costs.

To ensure the results are not driven by small firms, panel C shows that the portfolio return pattern is similar or stronger when firms in the lowest quintile by size are excluded.[32] Panel D shows that Fama and French (2015) five-factor model cannot fully explain the large and positive portfolio excess returns in panel A, especially for portfolios formed by inflexible firms with high operating leverage. For example, the monthly portfolio excess return decreases from 1.93% in panel A to 1.55% in panel D for the most inflexible firms with the highest operating leverage. More important, the alpha spread is still monotonically increasing from the most flexible quintile (40 basis points per month) to the most inflexible quintile (125 basis points per month), which is consistent with the excess return pattern in panel A.

Appendix B reports the results for the alternative sorts. Because our operating leverage measure requires 5 years of quarterly Compustat data, we can construct it for very few firms prior to 1980. However, we can build an analogous measure using Compustat annual data. This measure requires long historical windows (10 years) to perform our *QFC* estimation, and thus is very slow to reflect changes in operating leverage. However, annual data does permit us to construct the *QFC* measure for a reasonable number of firms as early as 1960. Table B2 shows that the basic interaction pattern in Table 9 is preserved in this longer sample.[33]

Tables B3 and B4 verify that the interaction effect is also observed when using alternative weighting schemes for the returns within the portfolios. Value weighting lowers the return spread between high and low operating leverage portfolios for all levels of flexibility. However, the strength of the operating leverage effect is still monotonically increasing in inflexibility. Using log asset or log market capitalization weighting strengthens the effect further, as does weighting by firm age. The results for these weighting schemes are also not sensitive to the sample period, and are preserved in the 1961–2016 period.

3.2 Return regressions

To control for other determinants of expected returns, we next consider regression specifications for individual stock returns. In this context, the hypothesis is that the slope coefficient of an interaction term between inflexibility and operating leverage should be positive and significant.

Table 10 reports the results for Fama and MacBeth (1973) regressions using monthly returns from 1980 to 2016. The baseline interaction test, Column (4), confirms the results from the two-way sorts in the previous subsection. In specifications (5) to (8), we include standard control variables, namely, reversal (*R01*), momentum (*R12*), book-to-market ratio (*BM*), market leverage (*ML*), and size (*SZ*). The variable $R01$ is the stock return over the previous month; $R12$ is the stock return over the 11 months preceding the previous month; *BM* denotes the log of the ratio of the book value of equity to the market value of

32 Below, we also verify that the interaction effect remains when we control for firm size in regression tests.

33 We thank the referee for suggesting this test.

Table 10
Fama-MacBeth return regressions

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
INFLEX		0.58***		−0.20	−0.32*	−0.23	−0.32*	−0.16	−0.40	−0.40
		(2.60)		(1.17)	(1.86)	(1.43)	(1.89)	(1.06)	(1.64)	(1.61)
QFC			0.74***	0.04	−0.17	−0.54***	−0.15	−0.48***	−0.29	−0.69**
			(3.57)	(0.20)	(0.93)	(2.93)	(0.85)	(2.65)	(1.03)	(2.19)
INTER				0.99**	0.97***	1.12***	0.91***	0.92***	1.19**	1.51**
				(2.45)	(2.63)	(3.14)	(2.70)	(2.80)	(2.19)	(2.55)
HN									−0.36	−0.35
									(1.42)	(1.48)
SKILL									0.81***	0.87***
									(3.24)	(3.31)
INTER2									−0.54	−0.65*
									(1.60)	(1.84)
R01	−1.85***				−1.89***	−1.85***	−1.78***	−1.77***	−1.85***	−1.83***
	(8.38)				(8.83)	(8.49)	(8.50)	(8.49)	(6.48)	(6.34)
R12	0.13				0.13	0.15	0.15	0.14	−0.11	−0.14
	(0.48)				(0.50)	(0.58)	(0.57)	(0.53)	(0.34)	(0.41)
BM	0.48**				0.62***	0.57***	0.51***	0.45**	0.50**	0.44*
	(2.42)				(3.64)	(3.21)	(2.99)	(2.52)	(2.23)	(1.96)
ML	0.09				0.17	0.25*	0.23	0.25*	0.53**	0.54***
	(0.58)				(1.20)	(1.69)	(1.55)	(1.78)	(2.41)	(2.76)
SZ	−2.07***				−1.89***	−1.94***	−1.71***	−1.77***	−2.15***	−2.10***
	(7.01)				(6.81)	(6.94)	(6.24)	(6.41)	(6.18)	(6.13)
R^2	3.5%	0.8%	0.5%	0.8%	3.8%	3.9%	4.1%	4.4%	4.3%	4.3%
N	872,488	872,488	872,488	872,488	872,488	803,529	753,686	691,154	825,932	755,326

This table shows results from Fama-MacBeth regressions of firm's excess returns on the measure of inflexibility (*INFLEX*), quasi-fixed costs over sales (*QFC*), and their product (*INTER*), as well as on controls for expected returns. Inflexibility is constructed using Compustat quarterly data as firm's historical range of operating costs over sales scaled by the volatility of the difference between the logarithm of sales over assets and its lagged value. The baseline measure of *QFC* is obtained by running 5-year (20-quarter) rolling-window regressions of operating costs on its first lag, contemporaneous sales, and lagged sales. *QFC* in the year following the 5-year estimation period equals the sum of regression intercept and predicted operating costs, scaled by sales. An alternative measure of *QFC* is constructed as the intercept from a 5-year (20-quarter) rolling-window regression of operating costs over total assets on sales over total assets, scaled by sales over total assets. We require firms to have at least ten quarterly observations for every 5-year window. Firm's hiring rate (*HN*) is defined as the percentage change in the number of employees. Industry-level labor skill variable (*SKILL*) is defined as the percentage of workers in the industry that belong to a high skill occupation. More details about those variables are provided in Belo et al. (forthcoming). *INTER2* is the product of *HN* and *SKILL*. *R01* is the stock return over the previous month; *R12* is the stock return over the 11 months preceding the previous month; *BM* denotes the log of the ratio of book value of equity to market value of equity; ML is the log of the market leverage ratio defined as book value of long-term debt divided by the sum of market value of equity and book value of long-term debt; and *SZ* is the log of the market value of equity. All variables are transformed into percentile rank form to minimize the impact of outliers. Specifications (5) and (6) use the baseline definition of *QFC* and the alternative definition of *QFC*, respectively; specification (7) uses the baseline definition of *QFC* from the rolling-window regression with 15 observations for every 5-year window; specification (8) uses the alternative definition of *QFC* with 15 observations for every 5-year window; specifications (9) and (10) use the baseline definition of *QFC* and the alternative definition of *QFC*, respectively. R^2 reported is the average value of R^2 from all monthly regressions. The coefficients are multiplied by 100. The sample period is from July 1980 to December 2016. t-statistics (based on Newey-West standard errors) are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

equity; *ML* is the log of the market leverage ratio defined as the book value of long-term debt divided by the sum of the market value of equity and the book value of long-term debt; and SZ is the log of the market value of equity. All variables are transformed into percentile ranks to diminish the possible influence of outliers. The coefficients are multiplied by 100 in the reported numbers.

When these controls are included, the coefficient on the interaction term, *INTER*, is positive and statistically significant and almost identical to Column (4). The magnitude of the coefficient is economically large: a value of 0.0097 corresponds to 97 basis points of monthly excess returns. Because the interaction term is the product of percentile ranks that range from 0 to 1, a coefficient of 0.0097 means that the return spread between the lowest and highest operating leverage firms is 97 basis points higher for the most inflexible firms than it is for the most flexible firms.

Moreover, in comparing specification (1) with specification (5), we observe that the coefficient estimates on *BM* are undiminished by the presence of our variables. Neither the unconditional inflexibility effect nor the conditional (interaction) effect with *QFC* significantly lowers the explanatory power of the book-to-market ratio, suggesting that the value effect is more likely driven by cross-firm differences in risk than by within-firm variation caused by quasi-fixed costs.

Specifications (6)–(8) report results for alternative measures of quasi- fixed costs over sales. Specification (6) uses the intercept scaled by sales over total assets from the rolling-window regression of operating costs over total assets on sales over total assets as *QFC*. Specification (7) uses the intercept plus the predicted costs from the rolling-window estimation divided by sales as *QFC*, and the minimum number of observations for every 5-year window increases from 10 to 15. Specification (8) uses the intercept scaled by sales over total assets from the rolling-window regression of operating costs over total assets on sales over total assets as *QFC*, and the minimum number of observations for every 5-year window increases from 10 to 15 as well. All coefficient estimates for the interaction term are reliably positive and statistically significant at the 5% level.

Belo et al. (forthcoming) document an interaction effect in returns that may be related to the one we show here. They first show a negative relation between firm's hiring rate and future stock returns, and then show that this effect is more pronounced in industries with relatively more high-skill workers than low-skill workers. As discussed in Section 3, they interpret higher worker skill as signifying higher firm adjustment costs. And, indeed, our variable *INFLEX* is positively correlated with their skill variable. If firm hiring is also negatively related to operating leverage, then it is possible that we are documenting the same effect.

We examine this possibility by including three additional variables in our regressions: firm's hiring rate (*HN*), industry-level labor skill variable (*SKILL*), and their interaction term (*INTER2*).[34] Specifications (9) and (10) report results when two different measures of *QFC* are used. As the table shows, the

[34] Firm's hiring rate is defined as the percentage change in the number of employees. Industry-level labor skill variable is defined as the percentage of workers in the industry that belong to a high skill occupation. The variable constructions parallel those in Belo et al. (forthcoming).

Table 11
Panel regression with double-clustered errors

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
INFLEX		0.72***		0.10	−0.20*	−0.14	−0.16*	−0.07	−0.18	−0.22
		(2.60)		(1.17)	(1.86)	(1.43)	(1.89)	(1.06)	(0.81)	(1.04)
QFC			0.83***	0.03	−0.17	−0.54***	−0.13	−0.45***	−0.14	−0.45*
			(3.57)	(0.20)	(0.93)	(2.93)	(0.85)	(2.65)	(0.55)	(1.72)
INTER				1.04**	1.03***	1.21***	0.88***	0.97***	0.78**	1.06**
				(2.45)	(2.63)	(3.14)	(2.70)	(2.80)	(1.99)	(2.43)
HN									−0.29	−0.25
									(1.35)	(1.26)
SKILL									0.64***	0.69***
									(3.90)	(4.05)
INTER2									−0.56**	−0.69**
									(2.15)	(2.50)
R01	−1.70***				−1.68***	−1.64***	−1.53***	−1.52***	−1.50***	−1.48***
	(5.75)				(5.88)	(5.82)	(5.68)	(5.55)	(5.71)	(5.92)
R12	0.18				0.23	0.24	0.24	0.22	0.25	0.19
	(0.56)				(0.53)	(0.51)	(0.60)	(0.54)	(0.71)	(0.65)
BM	0.66***				0.81***	0.75***	0.70***	0.61***	0.69***	0.58***
	(3.14)				(4.96)	(4.67)	(4.08)	(3.09)	(4.58)	(3.87)
ML	0.15*				0.26***	0.30***	0.328***	0.33***	0.55***	0.51***
	(1.93)				(3.82)	(3.66)	(3.88)	(3.81)	(3.82)	(4.02)
SZ	−2.22***				−2.05***	−2.09***	−1.85***	−1.89***	−1.73***	−1.70***
	(7.56)				(7.89)	(7.91)	(7.45)	(7.41)	(7.19)	(7.08)
R^2	0.9%	0.4%	0.5%	0.9%	0.9%	0.8%	0.8%	0.9%	0.7%	0.7%
N	872,488	872,488	872,488	872,488	872,488	803,529	753,686	691,154	825,932	755,326

This table shows results from panel regressions of firm's excess returns on the measure of inflexibility (*INFLEX*), quasi-fixed costs over sales (*QFC*), and their product (*INTER*), as well as on controls for expected returns. Inflexibility is constructed using Compustat quarterly data by firm's historical range of operating costs over sales scaled by the volatility of the difference between the logarithm of sales over assets and its lagged value. The baseline measure of *QFC* is obtained by running 5-year rolling-window regressions of operating costs on its first lag, contemporaneous sales, and lagged sales. *QFC* in the year following the 5-year estimation period equals the sum of regression intercept and predicted operating costs, scaled by sales. An alternative measure of *QFC* is constructed as the intercept from a 5-year rolling-window regression of operating costs over assets on sales over total assets, scaled by sales over total assets. We require firms to have at least ten quarterly observations for every 5-year window. Firm's hiring rate (*HN*) is defined as the percentage change in the number of employees. Industry-level labor skill variable (*SKILL*) is defined as the percentage of workers in the industry that belong to a high skill occupation. More details about those variables are provided in Belo et al. (forthcoming). *INTER2* is the product of *HN* and *SKILL*. *R01* is the stock return over the previous month; *R*12 is the stock return over the 11 months preceding the previous month; *BM* denotes the log of the ratio of book value of equity to market value of equity; *ML* is the log of the market leverage ratio defined as book value of long-term debt divided by the sum of market value of equity and book value of long-term debt; and *SZ* is the log of the market value of equity. All variables are transformed into percentile rank form to minimize the impact of outliers. Specifications (5) and (6) use the baseline definition of *QFC* and the alternative definition of *QFC*, respectively; specification (7) uses the baseline definition of *QFC* from the rolling-window regression with 15 observations for every 5-year window; specification (8) uses the alternative definition of *QFC* with 15 observations for every 5-year window; specifications (9) and (10) use the baseline definition of *QFC* and the alternative definition of *QFC*, respectively. The coefficients are multiplied by 100. Standard errors are clustered by firm and time (year and month). The sample period is from July 1980 to December 2016. *t*-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

coefficient on *INTER* remains significantly positive, whereas the coefficient on *INTER2* is significantly negative. Hence, two interaction effects coexist, but are different from each other.

Next, we check if our results are robust to alternative error structures. We repeat the return tests in panel regression format using the same set of control variables, clustering standard errors by firm and time (see Petersen 2009). As seen in Table 11, our inferences about the interaction effect are economically and statistically unchanged in all the specifications with this format.

Finally, to address the concern that our Fama-MacBeth inferences may be affected by a generated regressor bias[35] in the standard errors, we follow Chaney, Sraer, and Thesmar (2012) who use bootstrapping to tackle this issue in a similar setting.[36] The bootstrap procedure ensures that any extra noise in the auxiliary regressions will translate into variability in the Fama-MacBeth standard errors. We can thus compare the unadjusted standard errors from Table 10 with the realized standard deviation of the coefficient estimates across bootstrapped samples, and with the mean of Fama-MacBeth standard errors across the samples. Table B5 (see the appendix) presents the analysis. The average standard errors across bootstrapped samples are indeed slightly higher than the unadjusted standard errors from Table 10 (but not high enough to affect statistical inferences). However, we also find that the unadjusted standard errors *overstate* the actual variability of the estimated coefficients across bootstrapped samples.

3.3 Industry-level inflexibility measure and factor loadings

Although the model's implications are at firm level, it is reasonable to conjecture that a firm's ability to adjust its scale relates to industry-wide features of physical and technological capital. To the extent that scale flexibility may be industry-specific, it is informative to construct an industry-level measure analogous to our firm-level measure (as described in Section 3.1). Portfolio excess returns and abnormal returns (i.e., five-factor alphas) for this industry measure of inflexibility are presented in panels A and B in Table 12, respectively.

As shown in panel A, the return spread between high and low operating leverage portfolios monotonically increases from 42 basis points per month in flexible industries to 73 basis points per month in inflexible industries. Comparing to the portfolio excess returns when firm-level inflexibility measure is used, the pattern is very similar, although the effect is a bit weaker. Panel B shows these excess returns cannot be explained by the Fama and French (2015) five-factor model. Thus, the model's implications are also confirmed using this industry-level inflexibility measure.

The next test combines information in the industry measures with firm-level equity return information. Specifically, we construct an inflexibility factor as the return spread between inflexible-industry and flexible-industry portfolios, which are formed based on sorts on industry inflexibility. Firms' loading on

[35] A bias may arise because we construct operating leverage measures via auxiliary rolling window regressions.

[36] The bootstrap is performed as follows: we first draw a random sample with replacement for each firm using Compustat quarterly data; then we construct the time-varying inflexibility measure (*INFLEX*) and the quasi-fixed operating cost measure (*QFC*) on this sample; then we merge all the data sets (CRSP monthly return data, Compustat annual data, the *INFLEX* measure, and the *QFC* measure) together; then we draw another random sample every month with replacement using this merged dataset to form the second-stage regression sample; and, finally, we run the monthly Fama-MacBeth return regressions with this sample. We repeat this procedure 50 times and obtain 50 coefficients and standard errors on each variable. Then we compute the standard deviation of the estimated 50 coefficients and the mean of the estimated 50 standard errors.

Table 12
Portfolio excess returns using industry-level measure and firm-level factor loadings

	QFC						
	L	2	3	4	H	H-L	t–stat
A. Portfolio excess return using industry-level measure							
INFLEX(L)	1.22	1.11	1.13	1.21	1.63	0.42**	(2.00)
2	1.13	1.07	1.23	1.23	1.65	0.52***	(2.70)
3	1.23	1.13	1.17	1.35	1.82	0.59***	(2.79)
4	1.07	1.00	1.23	1.39	1.79	0.72***	(3.89)
INFLEX(H)	1.07	1.09	1.20	1.36	1.80	0.73***	(3.82)
B. Five-factor alpha using industry-level measure							
INFLEX(L)	0.20	0.02	0.07	0.23	0.85	0.66***	(3.39)
2	0.26	0.17	0.33	0.43	1.07	0.81***	(5.20)
3	0.33	0.20	0.30	0.57	1.35	1.02***	(6.40)
4	0.25	0.06	0.36	0.63	1.33	1.08***	(7.06)
INFLEX(H)	0.07	0.09	0.16	0.37	0.87	0.80***	(5.13)
C. Portfolio excess return using firm-level factor loadings							
INFLEX(L)	1.14	1.09	1.37	1.56	1.72	0.58**	(2.25)
2	0.99	1.04	1.07	1.21	1.45	0.46***	(3.58)
3	1.11	1.05	1.19	1.26	1.53	0.42***	(2.83)
4	0.99	1.25	1.24	1.39	1.71	0.72***	(4.30)
INFLEX(H)	1.12	1.37	1.51	1.62	2.03	0.91***	(3.42)
D. Five-factor alpha using firm-level factor loadings							
INFLEX(L)	0.01	0.03	0.14	0.42	0.71	0.70***	(2.60)
2	–0.06	0.00	0.05	0.29	0.56	0.62***	(4.63)
3	0.15	0.09	0.25	0.38	0.77	0.62***	(4.31)
4	0.25	0.46	0.41	0.65	1.18	0.93***	(6.07)
INFLEX(H)	0.51	0.99	1.10	1.32	1.94	1.43***	(5.65)

This table reports the monthly excess returns (in percentage) of 25 portfolios sorted on firm-level quasi-fixed costs over sales (*QFC*) and two measures of inflexibility (*INFLEX*). The industry-level inflexibility measure is constructed as the historical range of aggregate operating costs over sales scaled by the volatility of the difference between the logarithm of aggregate sales over total assets and its lagged value. Industries are classified by Fama-French 48 industrial classification. An alternative firm-level inflexibility measure is defined as firm's return loadings on the inflexibility factor, which is constructed as the return spread between inflexible-industry portfolios and flexible-industry portfolios. In particular, industries are sorted into three groups (bottom 30%, middle 40%, and top 30%) based on the ranked values of the inflexibility measure. Industries with the lowest 30% and highest 30% inflexibility measure form the flexible-industry portfolio and inflexible-industry portfolio, respectively. *QFC* is obtained by running 5-year (20-quarter) rolling-window regressions of operating costs on its first lag, contemporaneous sales, and lagged sales. *QFC* in the year following the 5-year estimation period equals the sum of regression intercept and predicted operating costs, scaled by sales. We require firms to have at least 10 observations for every 5-year window. Panels A and B report equally weighted portfolio excess returns and Fama and French (2015) five-factor alpha when industry-level inflexibility measure is used. Panels C and D report equally weighted portfolio excess returns and Fama and French (2015) five-factor alpha when firm-level factor loadings are used to proxy for firm's inflexibility level. The sample period is from July 1980 to December 2016. t-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

this factor can be computed as the regression coefficient of firms' monthly stock returns on the inflexibility factor. Portfolio test results using these factor loadings as a proxy for firm-level inflexibility are presented in panels C and D in Table 12. The fairly monotonic pattern of the return spread across inflexibility quintiles again confirms our main findings. Specifically, the return spread is 58 and 91 basis points per month for the most flexible firms and the most inflexible firms, respectively.

Taken together, the return tests in this section support the hypothesis that there is a positive interaction effect between scale inflexibility and operating leverage in determining expected stock returns. In the context of the model, flexible firms' contraction options become more valuable as operating leverage rises, lowering exposure to fundamental (priced) risk and reducing expected stock returns, whereas inflexible firms with fewer (or more costly) contraction options can not reduce scale easily when operating leverage rises. Thus, firms with higher operating leverage are riskier when they are more inflexible.

4. Second Moment Evidence

Recall that, according to the model, the instantaneous volatility of the stock return, $VOL(Z)$, can be expressed as $-EER(Z)/(\rho\sigma_{\Lambda})$. If we assume $\rho < 0$, then equity return volatility should exhibit the same conditional patterns as expected returns do. In the preceding section, we tested the model's predictions about the real option effect on equity returns. Now, we provide further evidence by examining the real option effect on the second moments of expected returns.

Returning to the portfolios formed by two-way independent sorts on scale inflexibility and operating leverage, we compute average return volatility for each portfolio. Specifically, we calculate the volatility of each stock in the portfolio as the standard deviation of CRSP daily return over a one year time period and then use the average value of those volatility as the portfolio return volatility.[37] Panels A and C in Table 13 present the results.

As panel A shows, the return volatility pattern across portfolios closely resembles the return pattern in Table 9. More precisely, the portfolio return volatility monotonically increases as quasi-fixed costs over sales rises. This positive relation becomes more pronounced as firms become more inflexible. Specifically, the annualized high-minus-low portfolio return volatility is 0.09 for the most flexible firms with a t–statistic of 4.37, this value increases to 0.15 with a t–statistic of 9.64 for less flexible firms, and it further increases to 0.20 with a t–statistic of 13.68 for the most inflexible firms.

Panel C excludes 20% smallest size firms from the sample and shows similar volatility patterns. Specifically, the annualized high-minus-low portfolio return volatility monotonically increases from 0.10 for flexible firms to 0.16 for inflexible firms; meanwhile, the t–statistic rises from 6.12 to 12.29. Thus, our test results are not driven by small size firms.

Moreover, the model implies that systematic risk should follow the same pattern as the expected returns. To assess this prediction, we compute the average stock beta for each of the double sorted portfolios. We obtain the stock beta by running a rolling-window regression of monthly stock returns on the value-weighted market return over the previous 36 months. Panels B and D

[37] We also construct stock return volatility using daily return over a month and similar results are obtained.

Table 13
Annualized return volatility and average beta for 25 portfolios

	QFC						
	L	2	3	4	H	H-L	*t*–stat
A. Average stock return volatility							
INFLEX(low)	0.45	0.47	0.48	0.50	0.54	0.09***	(4.37)
2	0.45	0.47	0.49	0.53	0.53	0.08***	(5.56)
3	0.46	0.48	0.50	0.54	0.61	0.15***	(9.64)
4	0.49	0.50	0.52	0.57	0.67	0.17***	(10.10)
INFLEX(high)	0.52	0.55	0.57	0.62	0.72	0.20***	(13.68)
B. Beta							
INFLEX(low)	1.09	1.07	1.09	1.07	1.07	−0.01	(0.16)
2	1.14	1.07	1.12	1.13	1.08	−0.07*	(1.83)
3	1.12	1.15	1.13	1.20	1.26	0.14**	(2.31)
4	1.16	1.13	1.18	1.26	1.31	0.16***	(2.92)
INFLEX(high)	1.17	1.22	1.21	1.28	1.39	0.22***	(4.28)
C. Average stock return volatility, excluding 20% smallest size firms							
INFLEX(low)	0.42	0.44	0.45	0.47	0.52	0.10***	(6.12)
2	0.42	0.42	0.44	0.47	0.50	0.08***	(7.27)
3	0.42	0.44	0.45	0.48	0.53	0.12***	(8.20)
4	0.45	0.46	0.47	0.50	0.58	0.14***	(8.26)
INFLEX(high)	0.49	0.50	0.52	0.55	0.65	0.16***	(12.29)
D. Beta, excluding 20% smallest size firms							
INFLEX(low)	1.11	1.10	1.11	1.10	1.11	0.01	(0.15)
2	1.14	1.08	1.12	1.16	1.19	0.05*	(1.74)
3	1.16	1.18	1.18	1.23	1.31	0.16***	(2.68)
4	1.19	1.17	1.21	1.29	1.37	0.18***	(2.99)
INFLEX(high)	1.20	1.26	1.26	1.34	1.48	0.27***	(5.25)

This table reports annualized return volatility and average beta for each of the 25 double-sorted portfolios in Table 9. Inflexibility is measured by firm's historical range of operating costs over sales scaled by the volatility of the difference between the logarithm of sales over total assets and its lagged value. Firm-level estimates of *QFC* are obtained by running 5-year (20-quarter) rolling-window regressions of operating costs on its first lag, contemporaneous sales, and lagged sales. *QFC* in the year following the 5-year estimation period equals the sum of regression intercept and predicted operating costs, scaled by sales. We require firms to have at least ten quarterly observations in the 5-year window. Stock return volatility is constructed as the standard deviation of CRSP daily return data over one year time period, then the average annualized stock return volatility for each portfolio is reported in panel A. Stock beta is constructed as the regression coefficient on the market return from a regression of monthly stock returns on the monthly value-weighted market return over the past 36 months, then the average beta of each portfolio is reported in panel B. Panels C and D report the average annualized stock return volatility and average beta when firms in the lowest quintile by size are excluded from the sample. The sample period is from July 1980 to December 2016. *t*-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

in Table 13 report average portfolio betas for the full sample and the sample without the 20% smallest size firms, respectively.

As predicted, average portfolio betas follows the same pattern as average stock returns in Table 9. In other words, a firm's systematic risk as measured by the market beta increases as operating leverage and scale inflexibility increases. Moreover, the beta spread across *QFC* portfolios is almost monotonically increasing as inflexibility rises. For example, in panel B, the beta spreads for flexible, less flexible, and inflexible firms are –0.01, 0.14, and 0.22, respectively, with *t*–statistics of 0.16, 2.31, and 4.28, respectively. Panel D provides supportive evidence as well. The corresponding beta spread for flexible, less flexible, and inflexible firms are 0.01, 0.16, and 0.27, respectively, with t–statistics of 0.15, 2.68 and 5.25, respectively.

To summarize, the results from portfolio sorts on portfolio return volatility and market beta largely support the model's predictions with respect to the second moments of equity returns: return volatility and systematic risk display interaction effects similar to the ones found for stock returns. We therefore conclude that the presence and, in particular, cross-firm variation of real option effects is important for us to gain a better understanding of expected returns and risk.

5. Conclusion

Investment-based asset pricing highlights the role of irreversibility in determining firms' equity risk and expected return. We have augmented this line of research by examining the cross-sectional implications of heterogeneity in scale flexibility in a dynamic model of a firm with assets-in-place, contraction options, and expansion options. We have shown that the primary implication of the model is that, rather than determining the level of firm risk, inflexibility determines the conditional response of risk to changes in operating leverage.

Empirically, we have constructed a firm-level range measure for inflexibility that is directly motivated by the theory. Extensive validation tests relate the measure to other proxies for factor adjustment costs proposed in the literature. The measure is economically and statistically significant as a conditioning variable in investment regressions and thus represents a useful contribution in its own right.

The new measure has enabled us to confirm the important role that inflexibility plays in determining the effect of operating leverage. As predicted by the theory, we find the relation between operating leverage and stock returns is weak for flexible firms, and this relation becomes much stronger as inflexibility rises. Moreover, we find inflexibility is associated with higher expected returns when operating leverage is high. That is, we document an interaction effect between inflexibility and operating leverage on stock returns. We also find consistent evidence for second moments of stock returns (i.e., betas and volatilities).

Overall, our findings support the idea that real option values can significantly shape a firm's exposure to priced risk when operating conditions deteriorate or improve. That is, scale inflexibility not only affects a firm's optimal investment policy in good states but also alters a firm's disinvestment policy in bad states. As firms make other operating decisions related to, for example, debt policies, acquisition activities, hiring and firing of labor, and innovation, our easily reproducible range measure can be used to study how scale inflexibility affects these operating decisions. This would be a fruitful avenue for future research.

Appendix A. Model Solution

This appendix provides the system of equations to solve the model described in Section 2. The firm's objective is to increase or decrease its scale, A, to maximize the market value of its equity:

$$J(\theta,A)=\max_{A_u,u\geq t} \mathrm{E}_t\left\{\int_t^{\infty} \Pi(\theta_u,A_u)\ \Lambda_u/\Lambda_t\ du\right\}. \tag{A.1}$$

In terms of the rescaled state variable Z and the rescaled value function V, the task is to choose points G, L, U, and H on the positive z-axis to maximize V. Absence of arbitrage imposes the two value matching conditions (VMCs):

$$V(G)=V(L)+F_L L^{\gamma}+P_L(G-L), \tag{A.2}$$

$$V(H)=V(U)+F_U U^{\gamma}+P_U(H-U). \tag{A.3}$$

The first equation requires that the post-investment value of the firm is the pre-investment value plus the funds injected. The second imposes the same for pre- and post- disinvestment (note $H-U<0$). Given these, functionally differentiating with respect to the barrier positions yields the smooth-pasting conditions (SPCs) as necessary conditions of optimality. These are:

$$V'(L)=-\gamma\ F_L L^{\gamma-1}+P_L, \tag{A.4}$$

$$V'(G)=P_L, \tag{A.5}$$

$$V'(U)=-\gamma\ F_U U^{\gamma-1}+P_U, \tag{A.6}$$

$$V'(H)=P_U. \tag{A.7}$$

As described in the text, HJ show that, subject to some regularity conditions, the solution function V satisfies an ordinary differential equation, the form of whose solution is given by Equation (4). The constants that appear in the equation are:

$$B=1\Big/(\hat{r}+\gamma\delta+(\gamma-1)\mu^{RN}-\tfrac{1}{2}\gamma(\gamma-1)\sigma^2), \tag{A.8}$$

$$S=\hat{m}\Big/\big(\hat{r}+\delta\big), \tag{A.9}$$

$$\lambda_{P,N}=\Big(b\pm\sqrt{b^2+2(\hat{r}-\mu^{RN})\sigma^2}\Big)\Big/\sigma^2, \tag{A.10}$$

where $b=\mu^{RN}+\delta+\frac{1}{2}\sigma^2$, $\mu^{RN}=\mu+\rho\sigma\sigma_{\Lambda}$, $\hat{m}=m-\eta P_U$, and $\hat{r}=r+\eta$.

When (4) is plugged into each of the SPCs and VMCs, the result is a system of six equations in D_N, D_P, G, L, U, and H. The system is linear in the first two, given the last four unknowns. But the nonlinearity in the last four renders numerical solution necessary.

Appendix B. Additional Empirical Results

This appendix provides additional empirical results. Table B1 reports monthly portfolio excess returns with a test sample including all observations in the 1970s. Table B2 reports double-sorted results using measures constructed with Compustat annual data over the period of 1961 to 2016. Table B3 reports monthly portfolio excess returns using various weighting schemes over the period of 1980 to 2016. Table B4 reports monthly portfolio excess returns using various weighting schemes over the period of 1961 to 2016. Table B5 reports bootstrap analysis of Fama-MacBeth standard errors.

Table B1
Portfolio excess returns, including all observations in the 1970s

	QFC						
	L	2	3	4	H	H-L	t–stat
A. Baseline results							
INFLEX(L)	1.10	1.15	1.03	1.01	1.30	0.20	(0.65)
2	1.14	1.01	1.18	1.33	1.39	0.25	(1.38)
3	1.14	1.17	1.28	1.33	1.50	0.36**	(2.11)
4	1.08	1.21	1.21	1.41	1.66	0.58***	(3.40)
INFLEX(H)	1.06	1.42	1.48	1.32	1.92	0.86***	(3.63)
Panel B. Alternative definition of QFC							
INFLEX(L)	1.23	1.07	1.07	1.16	0.56	−0.67	(1.07)
2	1.19	1.30	1.00	1.24	1.38	0.19	(0.86)
3	1.17	1.35	1.33	1.21	1.39	0.22	(1.12)
4	1.30	1.30	1.17	1.48	1.63	0.33	(1.49)
INFLEX(H)	1.14	1.52	1.60	1.67	1.78	0.64***	(2.92)
C. Excluding 20% smallest size firms							
INFLEX(L)	1.18	1.22	1.23	1.27	1.43	0.24	(0.59)
2	1.16	1.19	1.36	1.38	1.47	0.31*	(1.87)
3	1.24	1.29	1.09	1.62	1.56	0.32***	(2.61)
4	1.23	1.21	1.35	1.54	1.94	0.71***	(3.72)
INFLEX(H)	1.31	1.41	1.73	1.53	2.14	0.83***	(3.55)
D. Fama and French (2015) five-factor alpha							
INFLEX(L)	0.17	0.23	0.10	0.09	0.47	0.30	(0.82)
2	0.18	–0.07	0.24	0.52	0.73	0.55***	(2.79)
3	0.22	0.24	0.34	0.45	0.93	0.71***	(4.13)
4	0.17	0.36	0.34	0.75	1.19	1.02***	(6.94)
INFLEX(H)	0.28	0.82	0.75	0.67	1.48	1.20***	(5.83)

This table reports monthly excess returns (in percentage) of 25 portfolios sorted on firm-level quasi-fixed costs over sales (*QFC*) and a firm-level measure of inflexibility (*INFLEX*), both of which are constructed with Compustat quarterly data. Inflexibility is measured by firm's historical range of operating costs over sales scaled by the volatility of the difference between the logarithm of sales over total assets and its lagged value. Firm-level estimates of *QFC* are obtained by running 5-year (20-quarter) rolling-window regressions of operating costs on its first lag, contemporaneous sales, and lagged sales. The baseline measure of *QFC* in the year following the 5-year estimation period equals the sum of regression intercept and predicted operating costs, scaled by sales. An alternative definition of *QFC* is constructed as the intercept from a 5-year (20-quarter) rolling-window regression of operating costs over total assets on sales over total assets, scaled by sales over total assets. We require firms to have at least ten quarterly observations in the 5-year window. In June of each year t, NYSE-, AMEX-, and NASDAQ-listed stocks are sorted into quintile portfolios based on the inflexibility measure. Independently, firms are sorted into quintile portfolios based on their estimated quasi-fixed costs over sales. Monthly returns on the resultant 25 portfolios are then calculated from July of year t to June of year t+1. Panels A and B report equally weighted portfolio excess returns when we use the baseline definition of *QFC* and the alternative definition of *QFC*, respectively. Panel C reports equally weighted portfolio excess returns when firms in the lowest quintile by size are excluded from the sample. Panel D reports portfolio abnormal returns (i.e., alpha), which are computed by running time-series regression of portfolio excess returns on risk factors in the Fama and French (2015) five-factor model. The sample period is from July 1971 to December 2016. t-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Table B2
Double-sorted results using measures constructed with Compustat annual data

	QFC						
	L	2	3	4	H	H-L	t–stat
A. Baseline results							
INFLEX(L)	1.14	1.13	1.06	1.12	1.23	0.08	(0.53)
2	1.14	1.08	1.19	1.12	1.29	0.15	(1.17)
3	1.00	1.13	1.14	1.14	1.16	0.16	(1.20)
4	0.89	0.91	1.05	1.10	1.33	0.44***	(3.58)
INFLEX(H)	1.00	1.00	1.05	0.98	1.49	0.49***	(2.58)
B. Alternative definition of QFC							
INFLEX(L)	1.26	1.19	1.10	1.13	1.21	−0.05	(0.23)
2	1.21	1.26	1.18	1.23	1.35	0.14	(1.09)
3	1.17	1.15	1.22	1.20	1.29	0.12	(0.80)
4	1.15	1.21	1.16	1.18	1.34	0.19	(1.60)
INFLEX(H)	1.00	0.93	1.35	1.34	1.47	0.47**	(2.31)
C. Excluding 20% smallest size firms							
INFLEX(L)	1.30	1.31	1.15	1.28	1.30	0.00	(0.31)
2	1.28	1.22	1.41	1.34	1.37	0.09	(1.23)
3	1.02	1.26	1.31	1.28	1.20	0.18	(1.36)
4	1.00	1.09	1.21	1.22	1.46	0.46***	(3.74)
INFLEX(H)	1.13	1.09	1.20	1.16	1.61	0.48**	(2.47)
D. Fama and French (2015) five-factor alpha							
INFLEX(L)	0.34	0.23	0.25	0.34	0.42	0.08	(0.48)
2	0.24	0.29	0.37	0.30	0.58	0.33**	(2.48)
3	0.15	0.26	0.36	0.36	0.44	0.29**	(2.05)
4	0.05	0.01	0.17	0.28	0.61	0.56***	(4.55)
INFLEX(H)	0.17	0.22	0.31	0.27	0.97	0.80***	(4.93)

This table reports monthly excess returns (in percentage) of 25 portfolios sorted on firm-level quasi-fixed costs over sales (*QFC*) and a firm-level measure of inflexibility (*INFLEX*), both of which are constructed using Compustat annual data. Inflexibility is measured by firm's historical range of operating costs over sales scaled by the volatility of the difference between the logarithm of sales over total assets and its lagged value. Firm-level estimates of *QFC* are obtained by running 10-year rolling-window regressions of operating costs on its first lag, contemporaneous sales, and lagged sales. The baseline measure of *QFC* in the year following the 10-year estimation period equals the sum of regression intercept and predicted operating costs, scaled by sales. An alternative definition of *QFC* is constructed as the intercept from a 10-year rolling-window regression of operating costs over total assets on sales over total assets, scaled by sales over total assets. We require firms to have at least five observations for every 10-year window. In June of each year t, NYSE-, AMEX-, and NASDAQ-listed stocks are sorted into quintile portfolios based on the inflexibility measure. Independently, firms are sorted into quintile portfolios based on their estimated quasi-fixed costs over sales. Monthly returns on the resultant 25 portfolios are then calculated from July of year t to June of year $t+1$. Panels A and B report equally weighted portfolio excess returns when we use the baseline definition of *QFC* and the alternative definition of *QFC*, respectively. Panel C reports equally weighted portfolio excess returns when firms in the lowest quintile by size are excluded from the sample. Panel D reports portfolio abnormal returns (i.e., alpha), which are computed by running time-series regression of portfolio excess returns on risk factors in the Fama and French (2015) five-factor model. The sample period is from July 1961 to December 2016. t-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Table B3
Portfolio excess returns using various weighting schemes, 1980–2016

	QFC						
	L	2	3	4	H	H-L	*t*–stat
A. Value-weighted excess return							
INFLEX(L)	0.72	0.76	0.61	0.71	0.69	−0.03	(0.19)
2	0.69	0.69	0.84	0.70	0.72	0.04	(0.13)
3	0.43	0.75	0.62	0.61	0.79	0.36	(1.47)
4	0.64	0.66	0.66	1.01	0.86	0.22	(1.31)
INFLEX(H)	0.68	0.79	0.84	0.93	0.92	0.24	(1.51)
B. log(marketcap)-weighted excess return							
INFLEX(L)	1.04	1.11	0.97	1.01	1.36	0.32	(0.85)
2	1.04	1.02	1.12	1.23	1.31	0.27	(1.46)
3	1.07	1.13	1.10	1.30	1.44	0.37**	(2.24)
4	1.00	1.10	1.14	1.28	1.56	0.55***	(3.00)
INFLEX(H)	0.94	1.33	1.24	1.26	1.70	0.76***	(3.46)
C. Assets-weighted excess return							
INFLEX(L)	1.06	1.11	0.98	1.05	1.34	0.28	(0.76)
2	1.03	1.00	1.12	1.21	1.34	0.30	(1.59)
3	1.06	1.14	1.08	1.26	1.36	0.30*	(1.85)
4	0.99	1.11	1.12	1.25	1.47	0.48***	(2.79)
INFLEX(H)	0.90	1.29	1.22	1.23	1.62	0.72***	(3.40)
D. Firm-age-weighted excess return							
INFLEX(L)	1.05	1.10	1.01	1.05	1.25	0.20	(0.55)
2	1.06	0.99	1.10	1.20	1.34	0.28	(1.48)
3	1.08	1.13	1.09	1.28	1.35	0.28	(1.65)
4	1.04	1.10	1.15	1.31	1.52	0.47***	(2.81)
INFLEX(H)	1.03	1.46	1.30	1.31	1.87	0.83***	(3.30)

This table reports monthly excess returns (in percentage) of 25 portfolios sorted on firm-level quasi-fixed costs over sales (*QFC*) and a firm-level measure of inflexibility (*INFLEX*), both of which are constructed using Compustat quarterly data. Inflexibility is measured by firm's historical range of operating costs over sales scaled by the volatility of the difference between the logarithm of sales over total assets and its lagged value. Firm-level estimates of *QFC* are obtained by running 5-year (20-quarter) rolling-window regressions of operating costs on its first lag, contemporaneous sales, and lagged sales. The baseline measure of *QFC* in the year following the 5-year estimation period equals the sum of regression intercept and predicted operating costs, scaled by sales. We require firms to have at least ten quarterly observations in the 5-year window. In June of each year t, NYSE-, AMEX-, and NASDAQ-listed stocks are sorted into quintile portfolios based on the inflexibility measure. Independently, firms are sorted into quintile portfolios based on their estimated quasi-fixed costs over sales. Monthly returns on the resultant 25 portfolios are then calculated from July of year t to June of year t+1. Panels A, B, C, and D report value-weighted portfolio excess returns, log(marketcap)-weighted portfolio excess returns, assets-weighted portfolio excess returns, and firm-age-weighted portfolio excess returns, respectively. Marketcap in month t is firm's market capitalization in month t-1. Assets is defined as the logarithm of firm's total assets. Firm age is defined as the number of years a firm exists in Compustat annual file. The sample period is from July 1980 to December 2016. t-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Table B4
Portfolio excess returns using various weighting schemes, 1961–2016

	QFC						
	L	2	3	4	H	H-L	*t*–stat
A. Value-weighted excess return							
INFLEX(L)	0.64	0.65	0.53	0.45	0.58	−0.06	(0.16)
2	0.78	0.61	0.49	0.56	0.54	−0.24	(1.20)
3	0.39	0.66	0.55	0.68	0.47	0.08	(0.38)
4	0.48	0.75	0.42	0.66	0.70	0.21	(1.50)
INFLEX(H)	0.50	0.57	0.46	0.48	0.70	0.20	(1.31)
B. log(marketcap)-weighted excess return							
INFLEX(L)	1.07	1.06	0.96	1.00	1.10	0.03	(0.24)
2	1.06	0.99	1.09	1.02	1.17	0.11	(0.89)
3	0.89	1.04	1.05	1.04	1.02	0.13	(1.05)
4	0.80	0.83	0.97	1.00	1.20	0.40***	(3.49)
INFLEX(H)	0.97	0.93	0.96	0.88	1.31	0.34*	(1.88)
C. Assets-weighted excess return							
INFLEX(L)	1.08	1.05	0.94	1.00	1.05	−0.03	(0.22)
2	1.05	0.97	1.05	1.01	1.13	0.08	(0.68)
3	0.87	1.02	1.01	1.00	0.97	0.10	(0.84)
4	0.76	0.85	0.96	1.00	1.13	0.37***	(3.39)
INFLEX(H)	0.98	0.92	0.95	0.86	1.31	0.33**	(2.25)
D. Firm-age-weighted excess return							
INFLEX(L)	1.12	1.07	0.97	1.12	1.09	−0.03	(0.21)
2	1.05	1.02	1.10	1.07	1.19	0.14	(1.10)
3	0.89	1.04	1.11	1.09	1.07	0.18	(1.45)
4	0.79	0.87	0.98	1.06	1.20	0.41***	(3.70)
INFLEX(H)	0.96	0.89	1.00	0.89	1.30	0.34**	(2.02)

This table reports monthly excess returns (in percentage) of 25 portfolios sorted on firm-level quasi-fixed costs over sales (*QFC*) and a firm-level measure of inflexibility (*INFLEX*), both of which are constructed with Compustat annual data. Inflexibility is measured by firm's historical range of operating costs over sales scaled by the volatility of the difference between the logarithm of sales over total assets and its lagged value. Firm-level estimates of *QFC* are obtained by running 10-year rolling-window regressions of operating costs on its first lag, contemporaneous sales, and lagged sales. The baseline measure of *QFC* in the year following the 10-year estimation period equals the sum of regression intercept and predicted operating costs, scaled by sales. We require firms to have at least five observations for every 10-year window. In June of each year t, NYSE-, AMEX-, and NASDAQ-listed stocks are sorted into quintile portfolios based on the inflexibility measure. Independently, firms are sorted into quintile portfolios based on their estimated quasi-fixed costs over sales. Monthly returns on the resultant 25 portfolios are then calculated from July of year t to June of year t+1. Panels A, B, C, and D report value-weighted portfolio excess returns, log(marketcap)-weighted portfolio excess returns, assets-weighted portfolio excess returns, and firm-age-weighted portfolio excess returns, respectively. Marketcap in month t is firm's market capitalization in month t-1. Assets is defined as the logarithm of firm's total assets. Firm age is defined as the number of years a firm exists in Compustat annual file. The sample period is from July 1961 to December 2016. t-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Table B5
Bootstrap analysis of Fama-MacBeth standard errors

	INFLEX	QFC	INTER
A. Without additional controls			
Data SE	0.1709	0.2000	0.4041
Bootstrap coef SD	0.1609	0.1627	0.2926
Bootstrap mean SE	0.2052	0.2177	0.4551
B. With additional controls			
Data SE	0.1720	0.1828	0.3688
Bootstrap coef SD	0.1763	0.1705	0.3163
Bootstrap mean SE	0.2056	0.2201	0.4230

This table compares the standard errors from the Fama-MacBeth regressions in Table 10 to those computed in a bootstrap exercise that follows Chaney, Sraer, and Thesmar (2012). The bootstrap is performed as follows: we first draw a random sample with replacement for each firm using Compustat quarterly data; then we construct the time-varying inflexibility measure (*INFLEX*) and the quasi-fixed operating cost measure (*QFC*) on this sample; then we merge all the data sets (CRSP monthly return data, Compustat annual data, the *INFLEX* measure, and the *QFC* measure) together; then we draw another random sample every month with replacement using this merged data set to form the second-stage regression sample; and, finally, we run the monthly Fama-MacBeth return regressions with this sample. We repeat this procedure 50 times and obtain 50 coefficients and Fama-MacBeth standard errors on each variable. *Data SE* is the unadjusted standard error from the Fama-MacBeth regressions in Table 10. *Bootstrap coef SD* is the standard deviation across bootstrapped samples of the coefficient point estimates. *Bootstrap mean SE* is the cross-sample mean of the Fama-MacBeth standard errors. Panels A and B show the results for regression specifications (4) and (5) in Table 10, respectively.

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