Inventory, Fixed Capital, and the Cross-Section of Corporate Investment*

Kirak Kim

University of Bristol

Abstract

Low adjustment cost for inventory implies that firms can optimally substitute inventory investment for fixed investment by weighing incremental gains against total costs of adjusting the two types of capital. I empirically show that such inventory dependence—arising due to adjustment-cost difference and substitutability—renders firms' fixed investment significantly less responsive to various measures of investment demand. An analysis from the allocation-of-funds standpoint reveals that in response to one additional dollar available, a high inventory-dependence firm spends 14 cents more (8 cents less) on inventory investment (fixed investment) than does a low dependence firm although the total allocation to investing activities is similar across the two types of firms. Overall, this article uncovers substantial firm heterogeneity in inventory dependence and its impact, there providing empirical guidance for accounting for it in one's analysis of corporate policy.

Keywords: inventory; corporate investment; adjustment cost difference; substitutability; real friction; finance constraints

JEL: G31; E22

*This research is partly based on my doctoral dissertation at Arizona State University. I thank Ilona Babenko, Tom Bates, Oliver Boguth, Mike Hertzel, and Yuri Tserlukevich for their guidance and encouragement. This paper also benefited from suggestions and comments from Vicente Cunat, Claudia Custodio, David Denis, Evan Dudley (FMA discussant), Denis Gromb, Inmoo Lee, Tim Loughran, and seminar participants at Arizona State University, City University of Hong Kong, Korea University, University of Bristol, and University of Reading. Please send correspondence to: Kirak Kim, School of Economics Finance and Management, University of Bristol, 12 Priory Road, Bristol, BS8 1TU, UK. Telephone: +44 117 394 1489. E-mail: kirak.kim@bristol.ac.uk

1. Introduction

It is a familiar idea in economics and finance that positive productivity news, possibly coupled with greater availability of funds, encourages firms' investment. However, despite a large volume of research examining various market imperfections, a debate has continued on what drives cross-sectional differences in firms' responses to such news (Fazzari et al., 1988; Kaplan and Zingales, 1997; Hubbard, 1998; Stein, 2003; Erickson and Whited, 2000; Alti, 2003). One thing that seems missing from this long-standing debate is a careful assessment of to what extent the observed investment behaviors are consistent with a more direct explanation based on real-side characteristics. I believe it is important to establish this benchmark before appealing to other effects. This paper fills this void in the literature by pursuing the first systematic investigation of an overlooked aspect, namely, the relative importance of inventory in a firm's operation (henceforth inventory dependence).[1] The underlying intuition is that the relative ease and low cost of adjusting inventory—compared with fixed capital (Feldstein and Auerbach, 1976; Ramey, 1989)—can provide firms with an incentive to use inventory investment as a means of responding to productivity news. Consistent with this intuition, I find that firm inventory dependence, even after controlling for financial constraints, renders fixed investment significantly less responsive to various measures of firm fundamentals, such as firm profitability, industry-wide growth, economic policy uncertainty, and financing sources.[2]

The main economic idea relates firms' investment decisions to adjustment costs and the substitution of factors of production. Given the difference in per-unit adjustment costs between fixed capital and inventory—variable capital that is less costly to adjust, as Ramey (1989) puts it—firms' dynamic optimization problem amounts to weighing the expected incremental gains in the future against the total adjustment costs to pay today. Insofar as the complementarity between factors of production is less than perfect, firms would find it suboptimal (unnecessarily costly) to adjust fixed capital and inventory always evenly when profit opportunities arise. The

[1] As will be discussed in more detail, a firm's inventory dependence refers to the extent to which the firm can opt to use inventory investment as a response to productivity news. A firm's inventory stock is materials and products held as invested assets—as is fixed capital—for the future use, not those processed and consumed in the current period (the latter portion corresponds to the firm's production costs).

[2] While my paper is related to the large literature on investment-cash flow relationship, the main prediction is not restricted to this particular association. It is well-known that average Q—an empirical proxy of marginal Q—performs poorly in the investment regression. As Poterba (1988) and Erickson and Whited (2000) note, a firm's cash flow can signal not only the current fund availability but also the future productivity news not properly captured by Q. It is thus widely documented that investment responds strongly to cash flow or similar profitability measures in the regression that controls for Q. Below I discuss my findings as to internal funds in detail.

adjustment-cost difference and substitutability—imperfect complementarity—together result in some leeway that allows firms to choose inventory over fixed capital. Disproportionate investment in inventory is a cost-effective way to capture profit opportunities if adjusting both fixed capital and inventory results in total adjustment costs that outweigh incremental benefits. Therefore, a firm's inventory dependence—the extent to which a firm's operation enables the optimal use of inventory investment in capturing profit opportunities—lowers the firm's demand for fixed investment in response to productivity news.

To provide some insights on the notion of inventory as a factor of production rooted in the macroeconomics literature, I begin my study by surveying basic empirical facts about aggregate inventory investment. My analysis reveals a lead-lag relationship between aggregate inventory and fixed investments that highlights the forward-looking nature of firms' inventory behavior. This is consistent with the strong procyclicality of aggregate inventory growth well-documented in the literature (Blinder and Maccini, 1991; Ramey and West, 1999). Moreover, industry-level statistics and firm-level anecdotes indicate substantial cross-sectional heterogeneity in firm inventory dependence that motivates my investigation.

Since a direct application of the discussed idea is unavailable in the literature, I first formalize the effect of inventory dependence in a neoclassical investment model. The model contains the bare minimum features necessary to understand the impact of inventory dependence in a frictionless setting and to motivate my empirical work. Firms in my model optimize their investment decisions over inventory and fixed capital as factors of production (Christiano, 1988; Belo and Lin, 2012; Jones and Tuzel, 2013). Although financing is available without frictions, the relatively low adjustment cost for inventory implies that it is optimal for firms to adjust inventory first in response to productivity shocks. When a firm receives productivity news, the tradeoff in the firm's problem can be described as follows: By adjusting inventory only, the firm can save on total adjustment costs but must forego the gains to incremental outputs from investing in both factors together. By taking into account its substitutability and adjustment cost differential, the firm thus exploits inventory adjustment until net gains disappear. A high inventory-dependence firm utilizes inventory adjustment even more extensively and, as a result, has an even lower sensitivity of fixed investment to variation in productivity. Moreover, a high inventory-dependence firm tends to have both a higher inventory to capital ratio and a greater volatility of inventory investment, because such a firm on average accumulates inventory stock more and adjusts it more frequently. Guided by these results, I use the information contained in these statistics to construct an empirical proxy for firm inventory dependence.

The results of a battery of empirical tests using a large sample of U.S. firms lend strong support to my prediction about the impact of inventory dependence. Specifically, my estimation results show that, when moving from the top to the bottom tercile of the inventory dependence measure, the response of fixed investment to profitability, industry-peer net asset growth or industry-peer sales growth increases by a factor of two to three. A "mirror image" of each of these results is obtained from the regressions of inventory investment.

Throughout my tests I ensure that my finding is not an artifact of financial constraints or other firm attributes. In empirical data, small and young firms tend to have a larger amount of inventory and a higher volatility of inventory investment. Along these lines, Dasgupta et al. (2018), whose model considers the stockout-avoidance motive for inventory-holding, demonstrate that firms, when shut out of external financing, hold more inventories and adjust them more intensively. However, it should be noted that the observed pattern is entirely consistent with firm optimality even in the absence of financial constraints. As discussed above and demonstrated in my model, it is beneficial for firms to adjust inventory as much as possible before adjusting fixed capital. This benefit, regardless of financing frictions, should be larger for a firm that has a higher inventory-capital substitutability.[3]

Of course, real-world firms face financial constraints and, therefore, it is important to control for this attribute in my empirical tests. I mitigate this issue by using several sample matching and partitioning procedures to analyze a pair of the low and high inventory-dependence groups matched on financial constraints and various other attributes (see Section 4 for the details of the dependent-two-way-sorting procedure and the propensity score matching method used). All of my empirical results are robust to using these matched samples. To clarify, these results should not be viewed as evidence casting doubt on a consensus in the literature that financial constraints affect firms' investment decisions. The main point to highlight here is that inventory dependence has a first-order effect, independent from that of financial constraints.

To provide evidence corroborating my main findings, I extend my analysis in several ways. An investigation of how firms' investment responds to economic policy uncertainty (Baker et al., 2016) provides further insight on the effect of inventory dependence. My results show that fixed

[3] It is worth noting that the real friction featured in Dasgupta et al.'s (2018) model can generate a similar effect. In their model, what motivates firms to hold inventories is the stockout cost and, therefore, as this cost gets bigger, a firm, whether it is constrained or not, should have a larger amount and a higher volatility of inventory.

investment (inventory investment) by low inventory-dependence firms is about twice (one-half) as sensitive to policy uncertainty as that of high dependence firms. While firms' investment demand in general increases when the uncertainty is low (Gulen and Ion, 2016), the two types of firms have different focuses in terms of the means of responding to variation in uncertainty.

In addition, to support the causal interpretation of my findings, I conduct two experiments by exploiting changes in industry-level input prices and changes in state investment tax credits, respectively, as shocks plausibly exogenous and specific to inventory investment and fixed investment, respectively. A decrease in input prices, as Ramey and West (1999) and Dasgupta et al. (2018) argue, encourages firms to hold more inventories, because these extra holdings enable firms to produce more at a lower cost; similarly, when input prices increase, firms can be better off by cutting inventory investment and outputs. In contrast, given that changes in input prices are largely supply-side news, these shocks are unlikely to have a strong impact on firms' fixed investment. Using large decreases (increases) in industry-level input-price indices as positive (negative) shocks to inventory adjustment, I show that these shocks have a significant impact on inventory investment, leaving fixed investment almost unaffected. Moreover, inventory adjustment by high inventory-dependence firms responds to these shocks in a more salient way than does that of low dependence firms.

The experiment based on investment tax credits (ITCs henceforth) lends further support. Given that ITC is tax deduction allowed for the costs of machines, equipment or production facilities, it should encourage firms' fixed investment although its effect on inventory investment is not warranted. My results show that increases in states' ITCs, as expected, have a positive effect on fixed investment. Moreover, this effect is concentrated among low inventory-dependence firms, consistent with the prediction that high inventory-dependence firms' focus is placed largely on inventory investment.

In my concluding analysis, I asses the implications of inventory dependence for firms' uses of their financial resources. I examine how an additional dollar of funds is allocated across firms' investing activities. From this allocation-of-funds perspective, my investigation of both fixed and inventory investments can be viewed as part of the estimation system that tracks the uses of internal funds (Gatchev et al., 2010; Chang et al., 2014). Although the development of my argument, for ease of exposition, abstracts from financing frictions, I do allow for the possibility that productivity news and the fund availability are likely correlated with each other and both can encourage firms' investment (Poterba, 1988; Erickson and Whited, 2000; Alti, 2003).[4] Even if the signal that motivates a firm's investment is about financial slack, rather than productivity, my main prediction continues to hold, because the manager of the firm must decide on which type of factor investment to allocate more resources to, and, in doing so, the firm's adjustment costs and the factor substitutability are arguably the key real-side constraints to consider in her decision. Using a measure of internal funds satisfying the flow-of-funds identity in a system-of-equations framework (Chang et al., 2014), I first show that the total allocation of one additional dollar of funds to investing activities—fixed investment, inventory investment, and net acquisition—is essentially the same between low and high inventory-dependence firms. Despite this similarity in the total allocation, however, a high inventory-dependence firm spends, for each additional dollar available, 14 cents more (8 cents less) on inventory investment (fixed investment) than does a low dependence firm. I find similar differences in firms' allocation of external financing sources (equity and debt issuances).

Uncovering firm heterogeneity in inventory dependence and its significant impact on the cross-section of corporate investment has broad implications for our understanding of firms' investment policy. This evidence points out, among others, that researchers who aim to evaluate the impact on firms' investment of an exogenous event or of changes in some fundamentals should be able to sharpen their analysis by matching the sample on firms' inventory dependence. My paper thus provides useful guidance for researchers studying corporate investment policy in a variety of contexts.

My work is also related to the large literature concerned with firms' uses of their financial resources. My findings provide a novel insight on the allocation of corporate resources across investing and financing activities by highlighting that such allocation varies across firms for the reason related to not just financial constraints but also real-side frictions.

The rest of the paper proceeds as follows. Section 2 discusses the basic facts about inventory investment. Section 3 presents the model simulation results and develops empirical predictions. Section 4 describes the data, the measurement, and the empirical model. Section 5 reports the main empirical findings. Section 6 presents additional robustness checks and Section 7 concludes.

[4] Several studies use a quasi-natural experiment to show that investment is sensitive to surges in discretionary funds (Blanchard et al., 1994; Rauh, 2006). Although firms' responses to cash windfalls can be viewed as evidence of financial frictions, this does not explain why in general investment responses vary across firms.

2. Basic Empirical Facts about Inventory Investment and Firm Heterogeneity

This section discusses some basic facts about inventory investment that motivate my study. Prior literature provides ample evidence that the aggregate-level inventory investment is strongly procyclical (Christiano, 1988; Ramey and West, 1999; Khan and Thomas, 2007), and due to this well-known business-cycle fact, inventory growth is commonly regarded as a leading indicator. Figure 1 reports aggregate investment dynamics that further highlight this view. Panel A reports the extent to which the cyclical components of inventory and fixed capital, respectively, move with that of GDP.[5] It shows that cyclical inventory typically starts responding to cyclical GDP with a lag of one quarter or two, whereas cyclical fixed capital does so with a lag of four quarters or more. The *lead effect* of inventory investment similarly shows up in the cross-correlogram of fixed-capital growth (measured at quarter t) and inventory growth ($t-12$ through $t+12$) reported in Panel B. The correlation coefficient of 0.75 at $t-2$, for example, indicates that half-a-year-lagged inventory investment is a strong predictor of current fixed investment. A positive association goes in both directions, because fixed investment also calls for inventory investment. Overall, one- to four-quarter lagged inventory investment exhibits a strong correlation with current fixed investment (using the cyclical components of each series yields a similar result).

[Figure 1 around here]

The lead-lag relationship shown in the aggregate data series strongly supports the idea that firms start with inventory investment in response to productivity news before undertaking fixed investment. It suggests that during the early stage of news, inventory investment plays a role as a substitute for fixed investment. Prior literature shows that inventory adjustment, although not costless, is substantially less costly than fixed-capital adjustment.[6] However, the relatively low adjustment cost for inventory investment is of little appeal to a firm unless the inventory-for-

[5] Data on fixed capital and inventory are from the Federal Reserve Statistical Release Z.1, Table B.103 Balance Sheet of Nonfinancial Corporate Business (fixed capital is the sum of equipment and nonresidential structures). To obtain the cyclical components, the data series are logged and detrended using the Hodrick-Prescott filter with the smoothing parameter 1,600.

[6] Feldstein and Auerbach (1976), Christiano and Eichenbaumab (1987), and Ramey (1989), among others, argue that the adjustment of a firm's inventory to a desired level typically takes less than a month. Altering the order quantities of materials incur handling costs and warehouse expenses, but these costs are arguably much smaller than those associated with installing and disposing of machines, production lines or structures that arise due to the interference with production, learning process, or fire sales.

capital substitution enables *value creation*, which may be achieved through increases in output, sales, or efficiency. Additional inventory holdings allow firms to cope with both expected and unexpected increases in their product demands, hence expediting sales and mitigating stock-out costs. Moreover, as Kydland and Prescott (1982, p.1350) note, investment in input inventory allows firms to increase the size of a production run and to reduce the idle time between batches in the production process, and therefore improves efficiency of firms' installed capacity.

Turning to the micro-level data from the Compustat, Figure 2 reports industry means of the within-firm 10th, 50th and 90th percentiles of inventory investment, scaled by lagged assets. Although the within-firm median is almost zero for all industries, the within-firm variation is considerably large. Consistent with the low-adjustment-cost argument, firms in some industries, when necessary, make sizable investment in inventory, as much as 10% of total assets. Similarly, the relatively low downward-adjustment cost for inventory, compared with that of fixed capital, enables firms to engage in disinvestment of inventory as much as investment.

[Figure 2 around here]

Moreover, the within-firm variation of inventory investment differs substantially across firms and industries, suggesting that the importance of the role of inventory is greater for some firms than for others. This cross-sectional heterogeneity in inventory dependence is in line with some priors about industry characteristics. For example, cement plants (SIC 3200–3299) and oil refineries (2900–2999) rely heavily on a continuous-flow system that always runs at full capacity and stops once or twice a year. With non-stop "pipeline-and-furnace" type processes, these firms can hardly capture productivity news using inventory adjustment alone. In contrast, manufacturers of automobile parts (SIC 3700–3799) or electronic components (3600–3699) are more likely to use a batch production process (or a mix of batch processes and flow ones), with which efficiency and total production costs can vary with the volume of inventory. In the Internet Appendix, I provide and discuss some anecdotal evidence taken from the Business section of firms' 10-K reports that sheds more light on firm heterogeneity along these lines.

The aggregate-, industry-, and firm-level evidence surveyed in this section, collectively, suggests that (1) firms use inventory investment as a substitute for fixed investment in the early stage of productivity news, and that (2) there is substantial cross-sectional heterogeneity in the significance of the roles played by inventory in firms' operations.

3. Model Simulations and Empirical Predictions

In this section, I carry out model simulations to formalize the economic intuition discussed and to motivate my empirical investigation. A Q-theoretic model with fixed capital and inventory is adapted from, among others, Belo and Lin (2012) and Jones and Tuzel (2013). I begin with a brief summary of the key assumptions of the model, and provide discussions of the main findings from the simulation. Appendix A describes the model calibration and the numerical procedure.

3.1. Model Setup and Assumptions

The model is a partial-equilibrium one and the economy consists of a large number of firms that produce a homogenous good in a competitive market.

Production Technology. Each firm generates profits Π_t according to the constant elasticity of substitution (CES) production function

$$\Pi_t \equiv F\left(X_t, K_t, N_t\right) = e^{X_t}\left[s_k K_t^{-\gamma} + \left(1 - s_k\right) N_t^{-\gamma}\right]^{\frac{-\alpha}{\gamma}} - f \ , \tag{1}$$

where X_t is firm productivity, K_t is fixed capital, N_t is inventory, f is fixed operating costs, α is the degree of returns to scale, s_k is the relative weight of capital, and γ determines the elasticity of substitution $\text{ES} = (1+\gamma)^{-1}$ between capital and inventory.[7] The firm index i is suppressed for notational simplicity. As discussed in Appendix A, I restrict my attention to the case in which $\gamma > 0$ (ES < 1).

Laws of Motions. Firm productivity has a stationary and monotone Markov transition function $p_x\left(X_{t+1}|X_t\right)$, and follows the first-order auto-regressive (AR(1)) process

$$X_{t+1} = \rho_x X_t + \sigma_x \epsilon_{t+1}, \tag{2}$$

where ρ_x is the persistence of productivity, σ_x is the conditional volatility, and ϵ_t is the random shock that is independently and identically distributed (i.i.d.) standard normal. The laws of

[7] As $\gamma \to -1$ (ES $\to \infty$), the bracket term in (1) collapses to a linear function $\left[s_k K + \left(1-s_k\right)N\right]^{\alpha}$; as $\gamma \to 0$ (ES $\to 1$), it becomes a Cobb-Douglas one $\left[K^{s_k} N^{1-s_k}\right]^{\alpha}$; and as $\gamma \to \infty$ (ES $\to 0$), it becomes a Leontief one $\left[\min\{K, N\}\right]^{\alpha}$.

motions of capital and inventory are given by

$$K_{t+1} = (1-\delta_k) K_t + I_t^K \tag{3}$$

$$N_{t+1} = (1-\delta_n) N_t + I_t^N, \tag{4}$$

where I_t^K and I_t^N are gross investments that can be either positive, zero, or negative. The positive constants δ_k and δ_n are the depreciation rates, with $\delta_k < \delta_n$.[8]

Adjustment Costs. Factor adjustment is subject to convex costs, given by

$$G\left(I_t^K, K_t\right) = \frac{c_k}{2}\left(\frac{I_t^K}{K_t}\right) K_t \tag{5}$$

$$H\left(I_t^N, N_t\right) = \frac{c_n}{2}\left(\frac{I_t^N}{N_t}\right) N_t, \tag{6}$$

where c_k and c_n are the non-negative cost parameters, with $c_k > c_n$.[9]

Net Payoff. The firm is all-equity financed and its net payoff is defined as

$$D_t \equiv F\left(X_t, K_t, N_t\right) - I_t^K - I_t^N - G\left(I_t^K, K_t\right) - H\left(I_t^N, N_t\right). \tag{7}$$

Denoting by r the constant discount rate and $V_t \equiv V\left(X_t, K_t, N_t\right)$ the cum-dividend firm value, one can write the firm's problem as

$$V_t = \max_{\left\{I_t^K, I_t^N\right\}} \sum_{\tau=0}^{\infty} \mathbb{E}_t \frac{D_{t+\tau}}{(1+r)^{\tau}}, \tag{8}$$

subject to (1)–(7). The firm value then can be expressed in a recursive form (Bellman equation):

$$V_t = \max_{\left\{I_t^K, I_t^N\right\}} D_t + \mathbb{E}_t \frac{V_{t+1}}{1+r}. \tag{9}$$

Using Equation (9) and the assumptions outlined, I solve for the firm's optimal investment policy

[8] As discussed in Appendix A, the depreciation of inventory stock is due to obsolescence and deterioration, and differs from the costs of materials used in the current period, which are captured as production costs in firms' production function and profits Π_t.

[9] The form of the cost functions (5) and (6), while standard in the literature, abstracts from nonconvexity and costly reversibility (Abel and Eberly, 1994). But, even in the absence of these additional real frictions, the key stylized facts are reproduced in the model: Investment in fixed capital is "lumpy" and disinvestment is rare, because, in the majority of states, inventory adjustment first comes into play and captures shocks, keeping the demand for capital adjustment low. Adding noncovex costs and the wedge between purchase and sale prices penalizes fixed investment even more, thus encouraging the inventory-for-capital substitution more.

as functions of X_t, K_t, and N_t. Simulating shocks to firm productivity then yields the data on profits, market values, capital and inventory stocks, and investment in these factors.

3.2. Model Implication

To summarize the model's implication, a value-maximizing firm optimizes its investment decision over two factors of production, fixed capital and inventory. The productivity process X_t is persistent in the AR(1) sense and, therefore, the firm's factor adjustment responds to current productivity.[10] The per-unit adjustment cost of inventory is lower than that of fixed capital ($c_n < c_k$) and the complementarity between the two is imperfect ($\gamma < \infty$). In the model, these parameters determine the extent to which a firm is reliant on inventory. Intuitively, given the leeway for the firm to choose between the two types of investment, the adjustment-cost concern encourages inventory investment, hence reducing the demand for fixed investment. As a result, fixed investment is lumpy even in the absence of other frictions in the model. Moreover, inventory dependence weakens the responsiveness of fixed investment to variation in productivity.

Table 1 reports the simulation results to provide more insights. I solve the model with three different values of ES (0.25, 0.5 and 0.91, respectively, in Columns 1, 2 and 3), holding other parameters fixed. Panels A and B, respectively, report the model-generated moments and the investment regression results.[11]

[Table 1 around here]

There is an important observation to make from the summary statistics in Panel A: An increase in ES leads to increases in both the inventory-to-capital ratio N/K and the volatility of inventory investment $\sigma\left[I^N\right]$. This result provides useful information about a firm's substitution decision and inventory dependence. An inspection of the optimal investment rule can illuminate why this relationship shows up. Taking the first-order conditions with respect to I_t^K and I_t^N, respectively, for the right-hand-side of Equation (9) yields the conditions that establish a link

[10] See, for example, Gomes (2001) and Alti (2003) for the AR(1) representation of the productivity, cash flow, or demand process.

[11] The model, albeit parsimonious, does a good job replicating the key properties of real-side quantities. The median N/K ranges between 0.7 and 0.88, similar to the empirical data. The model delivers relatively large values for Q and relatively small values for the volatilities of factor investments compared with the empirical data. However, this is expected due to the absence of an aggregate shock in the model. Although the model overshoots Q, its medians are similar across the ES partitions, confirming that the ES per se has no systematic influence on the firm value in the model.

between marginal costs and benefits of investing:

$$1+\frac{\partial G_t}{\partial I_t^K} = \frac{1}{1+r}\int_X \left[\frac{\partial F_{t+1}}{\partial K_{t+1}} + (1-\delta_k)\left(1+\frac{\partial G_{t+1}}{\partial I_{t+1}^K}\right) + \frac{c_k}{2}\left(\frac{I_{t+1}^K}{K_{t+1}}\right)^2\right] p_x dX \quad (10)$$

$$1+\frac{\partial H_t}{\partial I_t^N} = \frac{1}{1+r}\int_X \left[\frac{\partial F_{t+1}}{\partial N_{t+1}} + (1-\delta_n)\left(1+\frac{\partial H_{t+1}}{\partial I_{t+1}^N}\right) + \frac{c_n}{2}\left(\frac{I_{t+1}^N}{N_{t+1}}\right)^2\right] p_x dX. \quad (11)$$

Equations (10) and (11) basically say that the firm chooses I_t^K and I_t^N such that adjustment costs today—the left-hand-side terms—equal expected gains. Given the functional form in Equation (5), the left-hand-side of Equation (10) becomes $1 + c_k \frac{I_t^K}{K_t}$ and this makes it clear that the larger the cost parameter c_k is, the more difficult to satisfy is the condition (10). The adjustment-cost gap $(c_k - c_n)$ thus encourages inventory investment.

Further inspecting Equations (10) and (11) reveals how substitutability affects firms' investment decisions. To describe this, write the expected marginal products as $\frac{\partial F_{t+1}}{\partial K_{t+1}} = \mathbf{m_1} s_k \alpha e^{X_{t+1}} K_{t+1}^{\alpha-1}$ and $\frac{\partial F_{t+1}}{\partial N_{t+1}} = \mathbf{m_2}(1-s_k)\alpha e^{X_{t+1}} N_{t+1}^{\alpha-1}$, respectively, where $\mathbf{m_1} = \left[s_k + (1-s_k)\left(\frac{N_{t+1}}{K_{t+1}}\right)^{-\gamma}\right]^{\frac{-\alpha}{\gamma}-1}$ and $\mathbf{m_2} = \left[1 - s_k + s_k\left(\frac{N_{t+1}}{K_{t+1}}\right)^{\gamma}\right]^{\frac{-\alpha}{\gamma}-1}$.[12] A firm's investment decision today affects the inventory-to-capital ratio next period $\frac{N_{t+1}}{K_{t+1}}$, which in turn influences $\mathbf{m_1}$ and $\mathbf{m_2}$ and thus the expected marginal products. However, when γ is small—i.e., ES is high—the variation in $\frac{N_{t+1}}{K_{t+1}}$ exerts little influence on the two terms (e.g., as $\gamma \to 0$, both $\mathbf{m_1}$ and $\mathbf{m_2}$ approach one). In other words, substitutability makes the inventory-to-capital ratio less relevant and thus gives a firm greater freedom as to the choice of factors to invest in.

With this leeway, a firm is faced with a tradeoff when productivity news arrives: By adjusting inventory only, the firm can save on adjustment costs, but must forego the gains to incremental outputs by investing in both factors together. The firm thus exploits inventory adjustment until net gains disappear. A large adjustment-cost gap and high ES allow firms to make use of inventory investment more extensively, there resulting in a larger variation in inventory investment $\sigma\left[I^N\right]$ and, on average, a higher ratio of N/K.[13]

Next I assess the impact of ES in a regression framework by estimating the investment equation

[12] Without $\mathbf{m_1}$ and $\mathbf{m_2}$, each reduces to the marginal product of the Cobb-Douglas production function.

[13] Jones and Tuzel (2013, p.574) report similar results from their model, noting that greater substitutability allows firms to respond to shocks mostly by changing inventory, while greater complementarity causes them to change both types of capital more evenly.

augmented with profitability (e.g., Fazzari et al., 1988; Gomes, 2001; Alti, 2003):

$$I_{i,t}^{K} = \lambda \Pi_{i,t} + \psi Q_{i,t-1} + a_i + \varepsilon_{i,t}, \tag{12}$$

where a_i is firm fixed effects and $Q_{i,t-1}$ is market to book ($V_{i,t-1}$ divided by the sum of $K_{i,t-1}$ and $N_{i,t-1}$). Firm profits $\Pi_{i,t}$ and fixed investment $I_{i,t}^{K}$ are scaled by the beginning-of-year book value. Note that $Q_{i,t-1}$ in this regression is average Q similar to the one used in empirical tests.[14] It is well-known that average Q deviates from marginal Q when firm technology is diminishing returns to scale (Hayashi, 1982; Cooper and Ejarque, 2003), and therefore, performs poorly in the investment regression. As noted by Poterba (1988), Erickson and Whited (2000), and Alti (2003), the poor performance of Q motivates cash flow or similar profitability variables in the investment regression even in the absence of financial frictions, because the persistence of productivity process implies that the current cash flow signals future productivity news not properly captured by Q. Similarly, profitability $\Pi_{i,t}$ in Equation (12), a function of productivity $X_{i,t}$, is expected to be more informative about investment demand than is average Q. On this ground, $\Pi_{i,t}$ is viewed as a signal for firms' investment decision in my investigation (using $X_{i,t}$ in place of $\Pi_{i,t}$ indeed leads to the same inference).

The estimation results reported in Panel B of Table 1 show that, as ES increases from 0.25 to 0.91, the coefficient λ drops from 0.18 to 0.11. The mechanism underlying these results is essentially the same as the one described above: A high-ES firm is more likely to let inventory investment respond to variation in productivity, keeping the demand for fixed investment low. As discussed, the adjustment-cost differential is another element necessary for the effect of inventory dependence to show up. When I carry out the same exercise by letting the inventory adjustment cost c_n vary while holding ES fixed, I obtain similar results (not reported).

3.3. Empirical Predictions

The model demonstrates that the substitutability and the adjustment-cost gap can generate substantial dispersion in firms' investment-responses to productivity news. It will be worth clarifying that inventory dependence should be understood as a notion deriving from the interaction of several real-side properties. As discussed, the adjustment-cost differential alone, no matter how large it is, cannot encourage inventory investment unless the nature of a firm's operation in the first

[14] Marginal Q is not readily available, because the partial derivative of V with respect to K is difficult to evaluate due to non-linearities and interdependence of K and N in the value function V.

place permits the substitution of inventory investment for fixed investment. Similarly, a firm's production capacity may be another determinant of inventory dependence; for instance, some, but not all, firms are able to create extra production capacity by hiring labor hours beyond the normal work schedule—without installing additional physical capital—and hence increase the output or profit per unit of capital.[15] Similarly, yet other attributes that are not modeled in this paper might have an interplay with substitutability and the adjustment-cost gap.[16]

However, given that these technology parameters are not directly measurable, incorporating *more* of them into my model is unlikely to yield additional insights for the empirical analysis. The model is nonetheless informative about how some observable variables, such as the volatility of inventory investment and the mean of inventory to capital, behave when the "deep" parameters change. These observable outcome variables can be useful in constructing an empirical proxy of firm inventory dependence. To the extent that the stylized model captures some key aspects of real-world firms' investment behaviors, the effect of inventory dependence should manifest itself in the empirical data. I aim to establish this in my empirical analysis.

In summary, my main prediction is that a firm's inventory dependence makes its fixed investment (inventory investment) less (more) responsive to firm- and industry-level profit opportunities or shocks to investment demand. Moreover, because my prediction does not preclude the possibility—although not explicitly modeled—that the availability of financing sources encourages firms' investment, I expect similar cross-sectional differences to show up in firms' allocation of financial resources across their investing activities.

4. Data, Measurement and the Empirical Model

This section introduces the data, the measurement, the sample partitioning procedures, and the baseline empirical model.

4.1. Data

The sample consists of the U.S. firms from the Compustat/CRSP merged file. My baseline sample includes manufacturing firms (SIC codes 2000–3999), because, like other Q-theoretic ones, my

[15] This extra capacity created should not be viewed as a firm's *unused* capacity. Related to this point, the Federal Reserve Board defines capacity as the "sustainable maximum output—the greatest level of output a plant can maintain within the framework of a realistic work schedule" for the publication of its capacity indices (Statistical Release, Table G.17).

[16] As discussed in the introduction, financial constraints can also play a role and thus, in my empirical tests, I use various sample matching procedures to ensure that inventory dependence is not an artifact of financial frictions or other unrelated attributes.

model can be better viewed as a description of these firms. Despite this common practice in the literature, it seems reasonable to apply my main prediction to other industrial firms that utilize inventory and fixed capital; as a robustness check, therefore, I experiment with an alternative sample consisting of non-regulated industrial firms (SIC outside the intervals 6000–6999, 4900–4999, and 9000–9999). I begin with the period of 1970–2015 but focus on that of 1980–2015 because of the use of the inventory dependence measure described below. Applying the data filters common in the literature, I obtain a panel of firms that: (1) have positive values for book assets (Compustat item name *at*), sales (*sale*), common equity (*ceq*), property, plant and equipment (henceforth PPE) (*ppent*), inventory (*invt*), and cash (*che*); (2) have book assets greater than $10 million in 2008 dollars; (3) have growth rates of assets and sales between –50% and 100%; and (4) have appeared in the sample in at least three consecutive years.[17]

4.2. Measurement and Sample Partitioning

4.2.1. The Empirical Measurement of Inventory Dependence

As discussed, the technological properties—substitutability and the adjustment-cost difference—determining a firm's inventory dependence are not straightforward to operationalize in an empirical setting and, therefore, I draw on the model simulation result to motivate an empirical measurement. As demonstrated in Section 3, an increase in inventory dependence brings about increases in the volatility of inventory investment $\sigma\left[I^N\right]$ and the ratio of inventory to capital N/K. These statistics are ex post informative about a firm's inventory dependence in the sense that they summarize the outcome of the firm's optimization over the two production factors. To construct an empirical proxy, I first calculate, for each firm, $\sigma\left[I^N\right]$ and $mean\left[N/K\right]$ from past ten years of data by requiring non-missing data for at least five years in each calculation window.[18] The empirical measurement of inventory dependence (henceforth $\text{NDEP}_{i,t}$ or NDEP suppressing firm and time subscripts) is then defined as the standardized value of the first principal-component of $\sigma\left[I^N\right]$ and $mean\left[N/K\right]$.

While this is the baseline construct of the NDEP measure with which I carry out my main empirical tests, I repeat my analyses using its several variants. Among these alternatives is a measure—otherwise the same as above—that is based on input inventory N^{inp}, instead of total

[17] The data filter (3), among others, is to ensure that firms in the sample are likely in a normal expansion path, a common assumption in investment models. The firm-years that display large swings in business fundamentals are more likely to have undergone significant reorganization, such as mergers and spin-offs.

[18] I winsorize I^N and N/K at 1% in both tails before calculating $\sigma\left[I^N\right]$ and $mean\left[N/K\right]$. I^N is inventory investment divided by the lagged assets.

inventory. The conclusion drawn from this alternative is the same as that from the baseline measure (see Section 6 for more details). I also perform additional checks with yet other alternatives, including the one based on the entire firm-level time-series data in place of the past ten-year data, gross PPE (Compustat item *ppegt*) in place of net PPE (*ppent*), or the volatility of inventory in place of that of inventory investment, as well as the industry-mean-adjusted measure. Using these alternatives yields qualitatively the same results (not reported).

4.2.2. Sample Partitioning and Matching Procedures

To investigate the impact of inventory dependence, I classify firms, in each year, into three groups of the introduced measure and check differences between the bottom and top terciles—i.e., low and high NDEP groups. As discussed in the introduction, a concern is that the two groups generated by the one-way-sorting procedure might differ in financial constraints. The absence of financing frictions in my model also calls for the need of controlling for financial constraints in my empirical tests. To address this issue, I employ the dependent-two-way-sorting method and the score-matching method.

The dependent-two-way-sorting procedure generates a pair of low and high NDEP groups that are matched on a proxy of financial constraints: Specifically, in the first round of the sorting procedure, firms each year are divided into *deciles* of a constraint proxy and, in the second round, the observations within each decile are re-ranked into terciles of the NDEP measure. Dividing the sample into deciles, instead of terciles, in the first-round sorting ensures that the chosen criterion is more accurately controlled for. I use various proxies, such as firm size, the credit rating-dummy, the dividend-payer dummy, the Kaplan-Zingales index (Lamont et al., 2001) or the Size-Age index (Hadlock and Pierce, 2010), as the first-round sorting criterion.[19] These proxies yield the same conclusion and, for brevity, I only report the results based on the Size-Age index (henceforth SA index) and the credit-rating dummy.

Furthermore, by using the propensity-score type matching method, I account for various other attributes that might differ across the low and high NDEP groups. Specifically, the sample is matched on the SA index, R&D intensity, cash flow volatility, Q, firm size and leverage ratio, as well as two-digit SIC industries and fiscal years. Cash flow volatility and R&D intensity are added to the score-matching criteria for the following reasons. Differences in the variance of cash flow

[19] When the credit-rating dummy is used, the sample is divided into two groups, the rated and the non-rated, in the first-round sorting.

across groups of firms, as demonstrated by Erickson and Whited (2000, pp.1049–1050), can drive cross-sectional differences in firms' investment response. Controlling for cash flow volatility also mitigates the concern that investment decisions can be influenced by idiosyncratic risk associated with firms' demands or business environments. Similarly, an R&D-intensive firm might hold a relatively small amount of fixed capital due to the fact that the firm's production is mainly outsourced and its R&D equipment is *expensed*, rather than capitalized. Such a firm is then more likely to be classified as a high NDEP firm although its business benefits little from inventory investment. Using the propensity scores estimated from the logit model, I perform one-to-one nearest-neighbor matching to select, for each high NDEP firm, a low NDEP one with the smallest possible score-difference, provided that the difference is within the caliper distance of 0.01.

4.2.3. Descriptive Statistics

Table 2 reports summary statistics of the selected variables. The first four columns report the mean and the 25th, 50th and 75th percentiles of each variable for the whole sample. Column 5 reports the medians for a pair of the low and high NDEP groups based on the one-way-sorted NDEP terciles. The pair in Column 6 is formed based on the dependent-two-way-sorted NDEP terciles, generated within each SA-index decile. All raw data items—i.e., those before the normalization—are inflation-adjusted to 2008 dollars and the normalized variables are winsorized at 1% in both tails. The variable definitions are provided in Appendix B.

[Table 2 around here]

The fact that the mean of I^N is close to zero might yield an impression that one could ignore inventory investment; however, its within-firm variation $\sigma\left[I^N\right]$ explains why it deserves attention. As expected, a typical firm in the high NDEP group exhibits much higher $\sigma\left[I^N\right]$ than does the low NDEP counterpart (Column 5). The difference stands out even after controlling for the SA index via the dependent two-way-sorting procedure (Column 6).

Figure 3 highlights this difference by zooming into within-firm statistics. For each firm, the 10th, 50th and 90th percentiles of I^N are calculated and the means of these percentiles are then reported for the low and high NDEP groups. Although the median I^N is close to zero, high NDEP firms' inventory investment swings as much as 12% of total assets, suggesting that inventory investment is a nontrivial part of corporate decision-making. Inventory investment by low NDEP firms varies in a smaller scale. One might suspect that firms are merely correcting the overshoot of their inventory from the previous year, making it bouncing back and forth, but the first-order autocorrelation of I^N is positive. Moreover, it is important to check whether a high NDEP firm simply has a larger within-firm variation in both types of investment. This concern is alleviated in the comparison shown in the right-hand-side panel of Figure 3: High NDEP firms exhibit a smaller variation in fixed investment than do low NDEP firms.

[Figure 3 around here]

In terms of various other firm characteristics reported in Table 2, the two groups look fairly similar. It appears that firms in the high NDEP group tend to have higher values for the SA index, R&D to assets and cash flow volatility, and lower values for the firm size, the leverage ratio and the number of years listed on the exchange.[20] However, these differences between the two groups shown in Column 5 are much smaller than the interquartile ranges of each variable. Once the sample is pre-sorted on the SA index, these differences become even smaller (Column 6). In addition, these differences disappear when the sample is matched on the propensity score based on various other characteristics discussed above (see Table 4, Panel C, for the matching results).

Additionally, Figure 4 reports the within-firm correlations of the cyclical components of inventory and fixed capital, respectively, with that of real GDP. The same procedure as in Figure 1, Panel A, is used to estimate the cyclical components for each firm with at least 30 quarters of valid data on inventory (*invtq*) and fixed capital (*ppentq*) from the Compustat quarterly tape. I then calculate, for each firm, the correlations with cyclical GDP. The medians of these firm-level correlations are reported for the low and high NDEP groups, respectively. The figure shows that the firm-level dynamics are consistent with the aggregate patterns reported in Figure 1: For both low and high NDEP groups, the response of cyclical inventory precedes that of cyclical fixed capital. Moreover, a comparison of the two groups provides prima facie evidence for the validity of NDEP as the empirical measure. The response of inventory is stronger among the high NDEP group than it is among the low one. In contrast, the lagged response of fixed investment is stronger among the low NDEP group.

[Figure 4 around here]

[20] Given that fixed capital remains more stable than inventory, a low inventory-dependence firm, with a relatively large amount of fixed capital, is more likely to have a large firm size.

4.3. The Empirical Model

To investigate firms' investment-responses to the measures of growth and profit opportunities, I estimate the following equations for the NDEP subsamples:

$$I^K_{i,t} = \lambda^k_1 x_{i,t} + \lambda^k_2 x_{i,t-1} + \Psi^k z_{i,t} + a_i + b_t + \varepsilon^k_{i,t} \tag{13}$$

$$I^N_{i,t} = \lambda^n_1 x_{i,t} + \lambda^n_2 x_{i,t-1} + \Psi^n z_{i,t} + a_i + b_t + \varepsilon^n_{i,t}. \tag{14}$$

where $I^K_{i,t}$ is fixed investment (capital expenditure minus the sale of physical capital) divided by the lagged assets $A_{i,t-1}$ and $I^N_{i,t}$ is inventory investment (change in inventory) divided by $A_{i,t-1}$. $x_{i,t}$ is the state variable, to which I will return shortly. The vector of covariates $z_{i,t}$ includes $Q_{i,t-1}$, the past 12-month excess stock return $R^{ex}_{i,t-1}$, the real firm size $\ln A_{i,t-1}$, and the book leverage ratio $Leverage_{i,t-1}$. I include firm fixed effects a_i to examine firms' responses to within-changes in the state variable $x_{i,t}$ absorbing other firm-specific unobservables. Year fixed effects b_t control for the unobservable variation in aggregate economic conditions.

To proxy for profit opportunities facing firms, I use the firm-level profitability and the industry-peer growth measures as the state variables $x_{i,t}$ in my baseline regressions. Profitability (cash flow to assets) has been widely used in the literature as a *complement* to the investment-Q regression. As discussed above, cash flow can signal both current fund availability and future profit opportunities and these two notions of cash flow have been well-established (Poterba, 1988; Erickson and Whited, 2000; Gomes, 2001; Alti, 2003).[21] These properties and the fact that marginal Q is unavailable, together, make firm profitability a suitable choice as a state variable in the investment regression.[22]

The growth of peer firms in the same industry is also a plausible signal for a firm to consider, because it may be informative about the demand state facing the firm. Although peer firms' growth may only be a coarse signal, an advantage is that it mitigates a mechanistic correlation between individual firms' own growth and investment. For firm i in industry j with M firms, I define industry-peer net asset growth $IndNAGR^{-i}_{i,j,t} = \frac{\sum_{m \neq i} NAGR_{m,j,t}}{M-1}$, where each firm in that

[21] In a similar vein, Abel and Eberly (2011) theoretically show that shocks to the user cost of capital cause investment to move in tandem with cash flow. Gala and Gomes (2016) demonstrate that such flow variables as cash flow or sales can be more informative about firms' investment demand than Q.

[22] My attempts to deal with the poor performance of average Q appear in the later section. Section 6 discusses the results estimated from the generalized methods of moments (GMM) recommended in the literature. Additionally, Internet Appendix, Table IA2, reports the results estimated from regressions that exclude Q. In all cases, I obtain the same conclusion.

industry is indexed by $m = 1, ..., M$ and $NAGR_{m,j,t}$ is net asset growth for firm $m \neq i$ (i.e., the corresponding firm i itself is excluded). $M > 5$ is required. I apply the same procedure to construct industry-peer sales growth $IndSGR^{-i}_{i,j,t}$.

The coefficients λ^k and λ^n in Equations (13) and (14) then estimate the responses of fixed investment and inventory investment, respectively, to productivity news. I examine whether and how significantly these responses differ across the low and high NDEP groups. As discussed, my prediction is that the response of fixed investment (inventory investment) should be weaker (stronger) among the high NDEP group. While many studies in this literature split the sample into subgroups to examine differences in the coefficient on a state variable, one could instead use an interaction of the state variable and the NDEP measure. Using this alternative approach yields similar results (reported in the Internet Appendix, Table IA1, Panel A). In Section 5, I introduce the variants of Equations (13) and (14) that correspond to different empirical designs.

5. Empirical Results

In this section, I empirically examine the impact of inventory dependence on the responsiveness of investment to productivity news. The discussed sample-matching procedures are applied to ensure that my results are not an artifact of the effect of financial constraints. I provide additional evidence by investigating economic policy uncertainty. To support the causal interpretation, I then conduct two experiments using changes in input-price indices and changes in investment tax credits as shocks specific to inventory investment and fixed investment, respectively. My concluding analysis is concerned with firms' allocation of internal and external financing sources.

5.1. Inventory Dependence and Differences in Investment Responses

5.1.1. Industry-Level Evidence

Given that firms' production technologies are likely to play an important role in their inventory-for-capital substitution decisions, cross-industry differences in inventory dependence are well-expected. My empirical investigation thus begins with the assessment of the industry-level association between the NDEP measure and investment responsiveness. Specifically, for each two-digit SIC industry, I estimate the regression coefficients on firm profitability using Equation (13). These coefficients are thus industry averages of the extent to which a firm's fixed investment responds to profitability. Figure 5 plots these industry mean responses against the industry mean NDEP.[23]

[Figure 5 around here]

In line with my main hypothesis, there is a strong inverse relationship: The response of fixed investment is overall weaker for industries with higher inventory dependence. Moreover, the coordinates of industries in this figure are broadly consistent with the industry-order shown in Figure 2 and the intuition discussed. Industries clustered in the northwest corner of the diagram—low NDEP and strong fixed-investment response—include stone and concrete (SIC 3200–3299) and oil-refining (2900–2999), whereas industries on the opposite include transportation (3700–3799) and electronic (3600–3699). As discussed, manufacturers of automobile parts or electronic components are more likely to benefit from inventory investment, with which these firms can save on setup costs, produce more outputs, and facilitate responses to customers' demand.

It is important to stress that despite this industry-level relationship, the NDEP measure exhibits large cross-firm variation within each industry. Consistent with this, previous studies in the operations-management literature have shown that manufacturing processes, production lead time, delivery lead time, supply-chain network, and storage capacity vary widely across firms and these attributes play important roles in determining firms' inventory behaviors (Lieberman and Demeester, 1999; Rumyantsev and Netessine, 2007). For example, two automobile parts manufacturers may be fairly different in types of products they make—hence different in production lead time, part delivery time, and the materials required—or in their warehouse capacity. Additionally, the two firms' businesses may involve different combinations of *make-to-stock* and *make-to-order* strategies. All of these factors are then likely to result in substantial differences in the two firms' inventory-holding decisions. In a similar vein, Zipkin (1991) argues that the optimal inventory strategy differs greatly across firms despite a casual intuition that large inventory is "inherently evil".[24] In sum, this line of research points to various factors related to manufacturing processes, product types, supply chain, and other organizational resources that give rise to firm heterogeneity in the significance of the roles played by inventory investment.

[23] Tobacco industry (SIC 2100–2199) has very few observations—the sample size is on average four firms per year—and has been excluded.

[24] Based on their empirical evidence, Hendricks and Singhal (2003, p.514) similarly emphasize that firms need to be cautious in cutting inventory buffers.

5.1.2. The Baseline Firm-Level Tests

Turning to the firm-level evidence, Table 3 reports the estimation results of Equations (13) and (14) based on the one-way-sorted NDEP subsamples. Panels A and B report the results for fixed and inventory investments, respectively. I examine firms' responses to variation in firm profitability (Columns 1 and 2), industry-peer net asset growth (Column 3), and industry-peer sales growth (Column 4). Each column contains a pair of the low and high NDEP groups. In the first row of each panel are the sum of the coefficients on the current and lagged state variables and the p-value associated with the difference between the two NDEP groups (Column 1 is an exception as the regression does not include the lagged variable).

[Table 3 around here]

The results show a sharp contrast between the two groups in their responses to state variables, consistent with my hypothesis. For example, the results reported in Panel A, Column 2, suggest that for a one-dollar increase in profitability, the response of fixed investment by a typical firm in the low NDEP group is more than twice as large as that of the high NDEP counterpart (0.20 vs. 0.08). The same conclusion is drawn from the results for the industry-peer net asset growth and sales growth. Given that industry peers' growth is a relatively coarse signal, overall weaker effects are expected in Columns 3 and 4. In Panel B, I test whether firm inventory dependence similarly generates cross-sectional differences in firms' inventory investment. The response of inventory investment to state variables is expected to be stronger among high NDEP firms and the results confirm this expectation. Across all columns, the response of inventory investment among the high NDEP group is two to three times as large as that of the low NDEP group.

In addition, the notable lead-lag relationship discussed in Section 2 shows up in the firm-level regression results. A comparison of the results reported in Panels A and B reveals that inventory investment mainly responds to a contemporaneous signal, whereas fixed investment responds to both current and lagged ones. For all cases, the response of fixed investment to a lagged state variable is similar to, or slightly larger than, its response to a current one, consistent with the extant studies that document delays in fixed investment up to several quarters (e.g., Montgomery, 1995). In contrast, inventory investment responds more strongly to current signals than to lagged ones, confirming the intuition that inventory investment is a quicker means of responding to productivity news. These results are reminiscent of the patterns shown in Figures 1 and 4.

The fact that this leading-indicator feature of inventory investment is confirmed in the firm-level investment dynamics lends further support to the notion of inventory dependence. During the early stage of productivity news, firms make use of inventory investment, as a substitute for fixed investment, in responding to their profit opportunities.

5.1.3. Controlling for Financial Constraints and Other Attributes

In Table 4, I employ several sample-matching procedures to address the concern that financial constraints or other attributes might have driven my findings. Specifically, the sample in Panel A is pre-matched on the SA-index deciles via the dependent-two-way-sorting procedure as described in Section 4. This means that the low NDEP group is a collection of ten low NDEP terciles taken from each decile of the SA index. In Panel B, the low NDEP group consists of two low NDEP terciles taken from both the rated and the non-rated groups. Moreover, the sample in Panel C is matched on the propensity score calculated based on the SA index, R&D intensity, cash-flow volatility, Q, firm size and leverage ratio, as well as two-digit SIC industries and years. As the data on bond ratings are available from 1986 in Compustat, the sample size decreases in Panel B; it further declines in Panel C because of the multiple matching criteria. To save space, the table only displays the sum of the coefficients on $x_{i,t}$ and $x_{i,t-1}$ and the p-value associated with the difference between the low and high NDEP groups.

[Table 4 around here]

Using these matched samples leads to the same conclusion as before. When the sample is pre-matched on the SA index, the coefficients in Column 1 of Panel A suggest that, in response to a one-dollar increase in cash flow, a low NDEP firm's fixed investment is 100% greater than that of a high NDEP firm; on the contrary, a low NDEP firm's inventory investment is only one third of that of a high NDEP firm. The conclusion remains the same when I examine industry-peer growth measures (Columns 2 and 3) or when I experiment with the credit-rating dummy as the pre-sorting criterion (Panel B). Turning to the score-matched samples in Panel C, I first confirm that the matching procedure generates a very similar pair of the low and high NDEP groups. As reported in subpanel C3, differences in means between the two groups are effectively zero for all matching criteria (p-values ranging between 0.33 and 0.94). The regression results in subpanels C1 and C2 show that despite this similarity in various characteristics, the impact of inventory dependence remains large and significant. In addition, the results also hold when the SA index and R&D intensity, as well as all other covariates, are directly controlled for in the regressions (see Internet Appendix, Table IA1, for details).

The matched sample results not only confirm the robustness of my finding, but also highlight one of the key messages of this paper: Even within each partition of finance-constraint proxies or various other firm characteristics, there is substantial firm-level heterogeneity in inventory dependence and thus in firms' investment-responses to the measures of investment demand. This heterogeneity is arguably an important aspect to take into account when researchers study corporate investment.

5.1.4. Example: Investment-Cash Flow Relationship and Firm Size and Age

I carry out two sets of comparisons between a group of small and young firms and that of large and mature firms to illustrate how one's conclusion can change once inventory dependence is accounted for. I examine differences in investment-cash flow relationship between the low and high SA-index groups and then check how these differences change once the two groups are matched on the NDEP measure.

[Figure 6 around here]

Figure 6 summarizes fixed-investment responses across the SA-index terciles (bar graphs represent the regression coefficients on profitability for each group). In Panel A, the SA-index subsamples are formed without pre-conditioning on the NDEP measure. Here the results are similar to the ones commonly found in prior literature: The coefficient among the low SA-index group—large and mature firms—is twice as high as that of the high SA-index group (0.19 vs. 0.08). Note that a positive relationship between these coefficients and the firm size and age, despite theoretical arguments usually predicting the opposite, has been well-documented in many empirical studies (see, e.g., Kaplan and Zingales, 1997; Cleary, 1999; Hadlock and Pierce, 2010; Chang et al., 2014).[25]

In contrast, these differences do not show up any more in Panel B, where the sample is pre-

[25] The opposite prediction—i.e., that the sensitivity of investment to internal funds is likely higher among small and young firms—is derived from several theoretical accounts in prior literature. Fazzari et al. (1988), among others, argue that constrained (small and young) firms invest only when internal funds are abundant, whereas unconstrained firms invest regardless of internal funds. Poterba (1988), Erickson and Whited (2000), and Alti (2003) point out that because cash flow contains long-run information not properly captured by Q, investment-cash flow relationship can be pronounced for firms for which measurement error in Q is large, usually small and young firms, regardless of financial frictions. Other explanations unrelated to a finance channel include a time-to-build friction (Tsoukalas, 2011) and the user-cost-of-capital information (Abel and Eberly, 2011).

matched on the NDEP measure (that is, the NDEP measure is used as the first-round sorting criterion and firms within each NDEP decile are divided into three SA-index groups in the second round). Here the results show that the coefficients are almost the same across three SA-index groups: Within the low (high) NDEP partition, the coefficients for the low, middle and high SA-index groups, respectively, are 0.17, 0.18 and 0.16 (0.10, 0.10 and 0.09). These coefficients also confirm, once again, a marked difference between the low and high NDEP groups.

These results suggest that a positive association between investment-cash flow sensitivities and firm size and age can be attributable in large part to the impact of inventory dependence on firms' investment policy. The results do not necessarily indicate that financial frictions are unimportant to firms' investment decisions. However, they do point to the importance of accounting for firm heterogeneity in inventory dependence when drawing inferences about corporate investment in various contexts.

5.2. Response to Economic Policy Uncertainty

In this subsection, I provide additional empirical support by investigating firms' responses to economic policy uncertainty. Since economic policies and regulations affect business environment in which firms operate, the uncertainty associated with these policies matters to firms' investment decisions. The real options literature suggests that firms have an incentive to delay their investment decisions until such uncertainty resolves (Dixit and Pindyck, 1994). Consistent with this theoretical prediction, recent studies show that firms increase investment when the level of uncertainty is low (Gulen and Ion, 2016; Jens, 2017; Julio and Yook, 2012).

To test whether inventory dependence leads to varying investment-responses to political uncertainty, I use the economic policy uncertainty index developed by Baker et al. (2016). They construct three types of underlying components, respectively, based on the volume of news articles containing the terms related to political uncertainty, the data on the tax codes set to expire in the near future, and the level of disagreement in the forecasts of CPI and government spending. The overall index is the weighted average of these three components, with the news-based index the most heavily-weighted.[26] When political uncertainty is low—i.e., when the uncertainty is resolved—firms in general are expected to invest more. But, in these low-uncertainty periods, fixed investment by a low NDEP firm is likely to be more salient than that of a high NDEP firm,

[26] I report results based on the news-based index, from which Gulen and Ion (2016) show most of the effect derives. The results are similar when the overall index is used.

which instead can make use of inventory investment more.

The equations estimated are as follows:

$$I_{i,t}^{K} = \theta^{k}\left(-\ln PU_{t}^{BBD}\right) + \Omega^{k} w_{i,t} + a_i + \varepsilon_{i,t}^{k} \quad (15)$$

$$I_{i,t}^{N} = \theta^{n}\left(-\ln PU_{t}^{BBD}\right) + \Omega^{n} w_{i,t} + a_i + \varepsilon_{i,t}^{n}, \quad (16)$$

where PU_{t}^{BBD} is Baker et al.'s news-based political uncertainty index, whose value ranges between 61 and 170 with a mean of 109 for the period of 1985–2015. I calculate the twelve-month average of the index from month $m-14$ through $m-3$, where m refers to a firm's fiscal-year-end month. These values are logged and then multiplied by minus one (hence $-\ln PU_{t}^{BBD}$) so that its interpretation can be consistent with that of other state variables used in the previous subsection. As the index is log-transformed, the coefficient θ^{k} is interpreted as how much a firm's fixed investment increases in response to a 100% increase in the certainty of the political circumstances or, equivalently, a halving of the uncertainty. As before, I include firm fixed effects a_i to estimate firms' responses to political uncertainty controlling for the firm-specific unobservables. I do not include year fixed effects, which would absorb all the explanatory power of PU_{t}^{BBD}.[27] To control for the variation in aggregate economic conditions, the vector $w_{i,t}$ includes, *inter alia*, GDP growth, calculated as the four-quarter compounded growth rate. It also contains cash flow to assets, as well as all other controls used before.

[Table 5 around here]

Table 5 reports the results for fixed investment (Panel A) and inventory investment (Panel B) with the one-way-sorted sample (Column 1), the dependent-two-way-sorted samples (Columns 2 and 3), and the propensity score-matched sample (Column 4). The results show that when economic policy uncertainty halves, a low NDEP firm increases fixed investment by 130–140 basis points (bps) but a high NDEP firm does so by 50–80 bps only.[28] In Panel B, the results are again in marked contrast with those in Panel A: In response to a halving of the uncertainty, a low NDEP firm increases inventory investment by 50–70 bps only, whereas a high NDEP firm increases it

[27] Strictly speaking, the index has non-zero cross-sectional variation for each year, because the fiscal-year-end months are not identical across firms. However, this variation is very small.

[28] These economic magnitudes are similar to those reported by Gulen and Ion (2016). They show an increase of 26 bps in quarterly investment, an annual equivalent of 104 bps, for a halving of the news-based index.

by 150–190 bps. Overall, these results support my hypothesis that inventory dependence has a first-order effect on firms' decision as to which type of factor investment to focus on.

5.3. Experiments Using Shocks Specific to Inventory Investment and Fixed Investment

In this subsection, I support the causal interpretation of my findings by exploiting exogenous shocks specifically impacting inventory investment and fixed investment, respectively. To clarify, an ideal natural experiment would be an event that exogenously shifts the cost of adjusting either inventory or fixed capital, rather than the one that affects investment opportunities. Such an event, if available, would provide an empirical setup analogous to, for example, the one in which the adoption of wrongful discharge laws serves as a shock to firms' firing costs (Autor et al., 2006). However, an event of this kind is not readily available for inventory or fixed capital, because the disinvestment of a firm's assets, unlike the firing of its employees, is usually not subject to laws. As an alternative approach, I rely on sources of variation in firms' incentives to invest. Importantly, I sharpen my analysis and the interpretation by using two different shocks, namely, industry-wide changes in input prices and state-wide changes in investment tax credits, that help establish a tighter link with inventory investment and fixed investment, respectively. I then show that firms' inventory dependence matters to how they respond to these shocks.

5.3.1. Input Price Shocks to Inventory Investment

Large changes in the prices of input materials can affect firms' inventory investment through the production channel (Ramey and West, 1999). A positive input-price shock (i.e., a decrease in prices) encourages firms to hold more inventories because these extra holdings of inventories allow firms to increase the production volume at a lower cost. Similarly, when input prices rise, firms are better off by cutting inventory investment and outputs. On the contrary, these input-price shocks, being supply-side news, are unlikely to have a strong impact on firms' fixed investment.

Following Dasgupta et al. (2018), I measure input-price shocks to inventory investment by using the industry-level indices for intermediate input prices from Bureau of Economic Analysis (BEA).[29] The input-price indices are plausibly exogenous to firms' investment policy because firm-specific productivity or investment policy is unlikely to determine the prices of input materials or

[29] The BEA's GDP-by-Industry data file (available at https://www.bea.gov/industry/gdpbyind_data.htm) includes Chain-Type Price Indexes for Intermediate Inputs by Industry. The annual price indices are available for three-digit NAICS industries from 1947–2017.

the price indices aggregated at the industry level. While some omitted factors, such as industry-wide investment opportunities or individual firms' bargaining power, might drive both input prices and firms' investment decisions, this potential omitted-variable bias problem is mitigated in several ways. First, I include industry-year fixed effects to absorb time-varying industry-specific news. For this purpose, I use Fama-French 48 industry classification, because the interaction of two-digit SIC and year dummies would remove variation in the BEA input-price indices almost completely (the indices are available at the three-digit NAICS level, which is roughly equivalent to two-digit SIC). In addition, by focusing my analysis on large changes in the input-price indices, I further alleviate the potential concern that some firms might have the ability (e.g., bargaining power) to lower the prices of input materials when they invest in inventories. Like before, time-varying firm characteristics are also controlled for. Other time-invariant unobservable factors are differenced out in the firm fixed-effects model. The equation estimated is as follows:

$$I_{i,j,t}^{N} = \beta_1 Positive_{j,t} + \beta_2 Negative_{j,t} + \Psi z_{i,j,t} + a_i + \left(b_t \times d_i^{FF48}\right) + \varepsilon_{i,j,t}, \tag{17}$$

where $Positive_{j,t}$ ($Negative_{j,t}$) is a dummy variable that equals one if a reduction in the BEA input-price index is above the top 30th percentile (below the bottom 30th percentile) for an industry j. As discussed, the interaction between year and Fama-French 48 industry fixed effects $b_t \times d_i^{FF48}$ is included.

Table 6 reports the results for both fixed investment (Panel A) and inventory investment (Panel B) although my main focus is on the latter. The results confirm the predictions discussed above: Firms' inventory investment responds to input-price shocks, whereas these shocks have almost no impact on firms' fixed investment (the coefficients in Panel A, except for Column 2b, are insignificant). The results in Panel B show that firms adjust their inventory stocks upward (downward) when there is a positive (negative) input-price shock. Importantly, the response to input-price shocks is much stronger among high NDEP firms, consistent with the results discussed in the previous subsections. These results continue to hold when financial constraints are accounted for in Columns 2–4.

[Table 6 around here]

The weak response to input-price shocks among low NDEP firms—for example, a cement manufacturer—can be understood as follows. Although decreases in the prices of silica sand and limestone are good news to a cement manufacturing firm, the incentive for the firm to increase these materials is likely *only moderate*, because the firm's such facilities as kilns and clinkers run 24 hours a day and stop only once or twice a year for essential maintenance. That is, this firm will need to build more of these facilities in order to benefit from increases in inventory holdings. Therefore, although a lower price in principle leads to a greater demand, the incentive to respond to input-price shocks by investing in inventory holdings is relatively small for these firms.

5.3.2. State Investment Tax Credits and Fixed Investment

Next I exploit changes in states' investment tax credits (ITCs) as exogenous variation in firms' incentive to undertake fixed investment. An ITC program allows firms to deduct a certain fraction of investment cost from their tax liability. Given that ITCs are allowed for the costs of machines, equipment or buildings, a positive effect on fixed investment of ITC is well-expected. However, inventory investment is not eligible for ITCs. Chirinko and Wilson (2008) show that an increase in ITC in a state has a positive impact on firms' capital formation and the number of establishments in that state. The staggered nature of changes in ITCs across states, along with the clear link between ITC and fixed investment, facilitates the interpretation of the results in a diff-in-diff setup. I then investigate the impact of inventory dependence on firms' varying responses. The following equation is estimated:

$$\Delta I_{i,s,t}^{K} = \gamma \Delta ITC_{s,t} + \Psi z_{i,s,t} + \Omega w_{s,t} + a_i + b_t + \varepsilon_{i,s,t}, \tag{18}$$

where $\Delta ITC_{s,t}$ is a variable that captures changes (mostly increases) in states' ITCs.

To examine the impact of ITCs, I use both dummy and continuous variables as follows: A dummy variable $ITC\ incr_{s,t}$ ($ITC\ decr_{s,t}$) equals one if ITC has increased (decreased) for a firm headquartered in state s in the year prior to the firm's fiscal year t; a dummy variable $ITC\ incr \geq 1\%$ ($ITC\ decr \geq 1\%$) equals one if an increase (decrease) is 1% or larger; and ΔITC is the magnitude of change in ITC. To account for states' economic conditions, $w_{s,t}$ includes state unemployment rate (Bureau of Labor Statistics Local Area Unemployment Statistics) and state real GDP growth (BEA Regional Economic Accounts). $z_{i,s,t}$ is the firm-level control variables. Year and firm fixed effects are included although the results without firm fixed effects are similar. As the main variable of interest is state-wide change in ITC, the standard errors are adjusted for clustering at the state level (Bertrand and Mullainathan, 2003). The state ITC data come from Chirinko and Wilson (2008), who conduct a comprehensive survey of the ITC programs for the period from 1964 to 2006. Between 1980 and 2006 (the sample period satisfying my data requirements), 25 states experience 32 ITC-increase events, among which 25 cases are an increase by 1% or larger. There are eight ITC-decrease events but only four cases are a decrease by 1% or larger. I obtain the historic firm headquarter location from the SEC EDGAR 10-K header information compiled by Bill McDonald and Tim Loughran.[30]

[Table 7 around here]

Table 7 reports the whole sample diff-in-diff results (Panel A) and the NDEP subsample results (Panels B–D). As before, I report the results for both types of investment although my focus is on fixed investment. The results first confirm that an increase in ITC has a positive effect on firms' fixed investment. Given the investment irreversibility, no relationship between ITC-decrease events and fixed investment is expected. Following Bertrand and Mullainathan (2003), I check the pre-treatment trends by using a set of four dummy variables: 1 $year\ before$ (0 $year\ before$) equals one if the state is about to increase ITC in one year (in the current year) and 1 $year\ after$ (2/3 $years\ after$) equals one if it had raised ITC one year ago (two or three years ago). The result confirms that firms' fixed investment responds to an ITC-increase event only after such a shock arrives but not before. Since change in investment is examined, a weak and insignificant coefficient on the dummy variable 2/3 $years\ after$ indicates that the *level* of firms' fixed investment remains as ITC programs continue. As expected, firms' inventory investment does not respond to ITC shocks.

Panels B–D then report the results for the NDEP subsamples (*ITC decr* and *ITC decr* $\geq$ 1% are not reported although included in the regressions). The results show that the impact of an ITC increase on fixed investment is concentrated among low NDEP firms. The weak response to an ITC increase among high NDEP firms suggests that fixed investment is relatively less important for these firms' business strategies, consistent with my findings in the previous subsections. Like before, the matched-sample results mitigate the concern that these varying responses might be driven by financial constraints or other characteristics.

Collectively, the results in this subsection buttress the idea that inventory dependence plays a significant role in determining how firms respond to the news that encourages investment. The

[30] Available from https://sraf.nd.edu/data/augmented-10-x-header-data/. For the early sample period for which the information is unavailable, the records in the earliest years (1994 for most firms) are backward-interpolated.

two exogenous shocks exploited here provide a tighter link with inventory investment and fixed investment, respectively. The results thus corroborate those based on the firm-level variables or economic policy uncertainty—a factor that influences firms' investment demand more broadly—used in the previous subsections.

5.4. Allocation-of-Funds Perspective

The financial accelerator-type argument—the idea that the increased availability of funds can encourage firms' investment—is a widely-held view, for which a large volume of literature has provided empirical support. Therefore, an important related question is whether inventory dependence has implications for firms' responses to their financing sources. Even if the information conveyed by a state variable is largely about financial slack, rather than productivity, my main hypothesis continues to hold, because a firm's inventory dependence would matter to the manager's decision as to how much of available funds to invest in inventory *and* capital stocks. By employing the flow-of-funds-identity approach, proposed by Gatchev et al. (2010) and Chang et al. (2014), I examine how firms allocate internal funds—measured by the variable *CFADJ* as defined below—across various activities. As an additional check, I examine firms' responses to external and internal financing sources.

5.4.1. Allocation of Internal Funds across Investing and Financing Activities

From an allocation-of-funds standpoint, my investigation of both fixed and inventory investments shares some commonality with the studies by Gatchev et al. (2010) and Chang et al. (2014). The main innovation of their work is the insight that a firm's uses and sources of funds must add up. The flow-of-funds identity leads to a system-of-equations approach that allows one to obtain a more complete picture concerning how firms allocate one additional dollar of internal funds across different activities.

To elaborate, a firm's budget constraint implies that in any given period, its uses of internal funds must satisfy the following identity:

$$\begin{aligned} CFADJ = I^K + I^N + NetAcquisition + \Delta ONWC + \Delta Cash + Dividend \\ -EquityIssue - DebtIssue - \Delta STDebt, \end{aligned} \tag{19}$$

where $CFADJ$ is the firm's internal funds available, measured as the sum of income before extra items, depreciation, extra items and discontinued operations, deferred taxes, equity in net loss, gains in sale of physical capital and investment, and other funds from operations, all taken from the statement of cash flows. The adjustment of these non-cash items, as emphasized by Chang et al. (2014), is important for the identity to hold more precisely. Unlike Chang et al. (2014), I do not subtract change in net working capital (henceforth NWC) directly from this measure, because inventory is part of the conventional definition of NWC (current assets minus current liabilities minus cash). Since I^N is already in Equation (19), an alternative for NWC is needed to satisfy the identity; therefore, other net working capital $ONWC$ is defined as NWC minus inventory. $ONWC$ hence can be viewed as, roughly, a firm's net position on receivables and payables. A firm's fund flows also include net acquisition expenditures (acquisition minus sale of investments), change in cash, dividends, and the fund flows to and from external financing.[31]

It is worth noting that Equation (19) is effectively the same as Chang et al.'s (2014, p.3,632), which consists of four fewer variables than mine. I could arrive at theirs if I had removed I^N and $\Delta ONWC$ by subtracting these two items directly from $CFADJ$, had combined I^K and $NetAcquisition$ into one variable, and had combined $DebtIssue$ and $\Delta STDebt$ together. Equation (19), a more disaggregated version, allows me to examine inventory investment separately.

Using the flow-of-funds identity (19), I then estimate a system of nine equations as follows:

$$y_{i,t}^{j} = \lambda^{j} CFADJ_{i,t} + \Psi^{j} z_{i,t} + a_i + b_t + \varepsilon_{i,t}^{j}, \tag{20}$$

where $y_{i,t}^{j}$ is one of the nine dependent variables, indexed by the superscript j, that are outlined in the identity condition above. These nine variables, as well as $CFADJ_{i,t}$, are scaled by the lagged assets $A_{i,t-1}$ and each regression includes firm and year fixed effects and the same control variables in $z_{i,t}$ as before.

Table 8 reports the results for the whole sample (Panel A) and the NDEP subsamples (Panels B–E). The column headers indicate the nine dependent variables from Equation (19). Each row displays, for brevity, the coefficients λ^j and standard errors only. In all cases, the impact of inventory dependence on firms' allocation of funds is consistent with the discussed economic intuition. The results show that, in response to a one-dollar increase in internal funds, a low NDEP firm on average (averaged across Panels B–E) allocates 15 cents to fixed investment but a high NDEP firm allocates only 7 cents. These figures flip for inventory investment: A low NDEP

[31] The sale of investments (siv) differs from that of physical capital ($sppe$); the former is the proceeds received by a firm when its investments in other firms or affiliates (e.g., unconsolidated subsidiaries) are sold.

firm's allocation to inventory investment is 9 cents, whereas that of a high NDEP firm is 23 cents.

[Table 8 around here]

It is important to stress that, despite these different focuses in terms of types of investment, the total allocation to investing activities, including net acquisitions, is very similar between the two types of firms. For one additional dollar of internal funds, low and high NDEP firms, respectively, spend 35 and 38 cents on fixed and inventory investments and net acquisitions.[32]

Compared with a low NDEP firm, a high NDEP firm allocates 9 cents more to $\Delta Cash$ and 4 cents more to $\Delta ONWC$. Thanks to these extra fund flows into and out of cash and other working capital, a high NDEP firm relies less on equity financing roughly by 15 cents than does a low NDEP firm. These differences seem plausible given that a high NDEP firm's resources are likely to flow more into and out of all working-capital components, not only inventory but also cash and other working capital, as these working-capital components can substitute each other.[33]

5.4.2. Internal Funds and External Financing Proceeds

I perform an additional check using $CFADJ$, net equity issuance, and net debt issuance as state variables in Equations (13) and (14). To clarify, a firm's capital-raising decision is in principle driven by its investment decision and, therefore, these regressions should not be viewed as claiming that equity or debt issuance *causes* investment in a deep sense. This exercise nonetheless allows me to assess how firms allocate one additional dollar raised from both internal and external financing. Although it is not impossible for one to motivate equity and debt issuances in these regressions by loosely appealing to a finance friction-type argument, the coefficients may be best interpreted as the proportion of issue proceeds allocated to investments.

[Table 9 around here]

Table 9 reports the results for fixed investment (Panel A) and inventory investment (Panel B). I include the same set of controls as before (not displayed). The results show that large differences

[32] I also test whether R&D investment affects my results by modifying Equations (19) and (20) to include R&D as an additional use of funds. The results confirm that firms' total allocation to investing activities, including R&D, are similar across the two groups (see Internet Appendix, Table IA3).

[33] In a similar vein, Gao (2017) demonstrates that firms' working-capital demand for cash holdings has an interplay with inventory holdings. She argues that the secular increase in corporate cash holdings through 1990s and 2000s may be attributable to not only an increase in the well-documented precautionary demand (Bates et al., 2009), but also an increase in the working-capital demand for cash holdings, in lieu of inventory holdings.

exist between the two NDEP groups in the coefficients on equity and debt issuances, as well as $CFADJ$. For example, the results reported in Panel A, Column 1, show that a low NDEP firm's allocation to fixed investment of each dollar raised from internal funds, equity issuance and debt issuance, respectively, is larger by 10, 3 and 3 cents than is that of a high NDEP firm and these differences are statistically significant at the conventional levels. Using the dependent-two-way-sorted or the score-matched samples yields similar results (Columns 2–4). The results for inventory investment (Panel B) are again a mirror image of those for fixed investment.

Overall, the results in this subsection confirm that inventory dependence affects the response of investment not only to productivity news but also to fund availability. As shown in the matched-sample results, the impact of this real-side attribute differs from that of financial constraints.

6. Further Robustness Checks and Other Considerations

6.1. All Industrial Firms with Data on Input-Inventory Investment

The baseline measure of inventory dependence is based on total inventory, which consists of both input inventory—raw materials (*invrm*) and work-in-process goods (*invwip*)—and finished goods (*invfg*). Casual intuition might suggest that only the adjustment of input inventory, but not that of finished goods, would have a direct link with a firm's real decision. However, given that a manufacturer's finished goods are the result of its in-house processing of materials and supplies, the adjustment of input inventory is inherently inseparable from its decision to adjust finished-goods inventory. Moreover, finished-goods inventory too plays productive roles, such as buffer stock for delivery, demonstration, or display, that help firms to capture their profit opportunities. For these reasons, total inventory may contain a fuller set of information concerning firms' investment decision than does input inventory.

Given the absence of theoretical guidance, I ensure that my findings are robust to using input inventory in place of total inventory. Specifically, I repeat my main tests using the sample of non-regulated U.S. firms (those with SIC codes outside the intervals 6000–6999, 4900–4999, and 9000–9999) that have valid input-inventory N^{inp} data and satisfy the data filters outlined in Section 4. Although this alternative sample includes more industries, the sample size rather drops by 30%, compared with that in Table 3. This is because the Compustat records are sparse for the subcomponents of inventory. I then construct an alternative measure, say, $\text{NDEP}_{i,t}^{inp}$, based on $\sigma\left[I^{N^{inp}}\right]$ and $mean\left[N^{inp}/K\ \right]$ in otherwise the same way as before. In addition, input-inventory investment $I_{i,t}^{N^{inp}}$ replaces total inventory investment as the dependent variable in Equation (14).

[Table 10 around here]

Table 10 reports the results for profitability (Panel A), industry-peer growth (Panels B and C), policy uncertainty index (Panel D), and internal and external financing sources (Panel E), together with different sample matching procedures as indicated in the column headers. The results are reassuring: In all cases, differences in coefficients between the low and high NDEP^{inp} groups are similar to those reported in the previous section, yielding the same conclusion as before.

6.2. GMM Estimation

It is a wide consensus that average Q used in empirical studies is a poor approximation of marginal Q and thus is a noisy measure of firms' true investment demand. Erickson and Whited (2000), among others, point out that the OLS coefficient on the mismeasured Q is biased downward and the bias is even larger when a relatively well-measured variable, such as profitability, is included in the regression. As discussed earlier, since firm profitability not only indicates the current fund availability, but also contains the long-run information about future productivity, it is a suitable state variable for the purpose of my study. Nevertheless, if an error-correction estimator can purge Q of the measurement error, this may change my inferences about the effect of inventory dependence drawn on profitability (cash flow to assets).

I employ two GMM estimators that have been commonly employed in the literature, namely, Arellano and Bond (1991) style dynamic panel GMM (henceforth AB-GMM) and the high-order GMM proposed by Erickson and Whited (2000, 2012) and Erickson, Jiang, and Whited (2014) (henceforth EJW-GMM). AB-GMM uses as instruments the information in the lags of the mismeasured variable. EJW-GMM exploits the information in the third and higher-order moments/cumulants.[34] I follow the procedures outlined in Almeida et al. (2010) and Erickson et al. (2014). To implement AB-GMM, I apply the first-difference transformation to data and estimate Equations (13) and (14) using the lagged levels of Q as instruments for the differenced Q; for the tabulated results, the second and third lags are used as instruments.[35] For the estima-

[34] The high-order moment estimator was originally developed by Erickson and Whited (2000). Erickson, Jiang, and Whited (2014) propose the cumulant estimator, which has better finite-sample properties.

[35] Roodman (2009) recommends the instrument matrix of a collapsed form, in which the columns for each time dimension are compressed (i.e., "zeros" removed). This approach restricts the instrument count and thus increases

tion of EJW-GMM, the data undergo the within-transformation; for the tabulated results, the fifth-order cumulant estimator is used.

[Table 11 around here]

Table 11 reports the AB-GMM results and the EJW-GMM results in Panels A and B, respectively. Like before, various sample-matching procedures are applied. These GMM approaches return the Q coefficients somewhat larger than those estimated from the OLS-type fixed-effects model in the previous sections. However, the cross-sectional differences in cash-flow coefficients are largely unaffected. In all cases, using the GMM estimators leads to the same conclusion as before.

6.3. Declining Trend in Investment-Cash Flow Relationship

Recent studies document a substantial decrease in investment-cash flow relationship over time. The decline may be attributable to several sources, including a decrease in the persistence of cash flow (Chen and Chen, 2012) and a decrease in the measurement quality of a conventional cash flow variable (Lewellen and Lewellen, 2016). This trend might indicate that as the persistence of a firm's productivity process gets lower, the manager views current cash flow as a less reliable signal about the firm's profit opportunities. Alternatively, there might have been a gradual shift in U.S. firms' focus from traditional investment—production capacity installed internally—to such alternatives as outsourcing or joint ventures.[36] While the current literature is inconclusive regarding what has caused this declining trend, I ensure that the effect of inventory dependence has not disappeared. To this end, I estimate cash flow coefficients for three different 12-year subperiods. The results, reported in the Internet Appendix, Table IA4, show that although there has been an overall declining trend in cash flow coefficients for both fixed and inventory investments, differences in these sensitivities across the NDEP groups remain significant even in the later sample period.[37]

---

estimation efficiency, as well as the computing speed.

[36] Although this conjecture is only tentative, Almeida et al. (2017), for example, suggest that a nontrivial portion of firms' production is outsourced through purchase obligations (PO), namely, legally-binding agreements to buy goods and services. The authors report that their PO sample firms on average have such outsourcing obligations as much as 20% of the costs of goods sold.

[37] I find the same pattern from the model simulation results: As the productivity persistence ρ_x drops, the regression coefficient on $\Pi_{i,t}$ declines but differences in this coefficient across ES partitions continue to show up (see Internet Appendix, Table IA5).

6.4. Potential Role of Labor

It is conceivable that the relative importance of variable-capital type labor—say, labor reliance—may similarly impact firms' fixed investment decision. However, such an effect is likely difficult to discover if one's empirical investigation is based on standard data sources that do not differentiate between types of labor. For example, although a firm that hires a large number of employees would be classified as a "high labor-reliance" firm, its variable-capital type labor (low-skill workers) might comprise only a small portion of the firm's workforce. In this case, likely central to the firm's business is investment in fixed capital *and* high-skill workers. Such a firm's fixed investment is then highly responsive to productivity news although the firm is—incorrectly—labelled as the high labor-reliance group. For this firm, high-skill workers presumably play an important role but their role differs from that of variable-capital type labor. It is well-known that labor adjustment costs are much larger for high-skill workers than for low-skill workers (see, e.g., Blatter et al, 2012; Belo et al., 2017). Therefore, skilled labor is unlikely a substitute for fixed capital in the context of conventional production.[38]

In my attempt to assess the effect of labor reliance, which I measure using the total employment from the Compustat, the problem discussed above seems to obscure the potential effect. The results show that there are relatively small differences in the responsiveness of fixed investment between the low and high labor-reliance groups—as mentioned, this classification is based on the Compustat information and is likely inaccurate—and that the differences are often insignificant (see Internet Appendix, Table IA6). This weak evidence is likely due to the fact that the number of total employees does not properly measure the relative importance of variable-capital type labor. Although not pursued here, an analysis that takes into account different types of labor might yield a more accurate description of the impact of variable-capital type labor.

6.5. Additional Checks

In addition, I check the robustness of my results to yet other potential concerns. In unreported results, I find that my conclusion remains unchanged when: (1) I exclude petroleum (SIC 2900–2999), paper mill (2600–2699), clothing (2300–2399) and leather (3100–3199) industries, which Figure 5 suggests might be outliers; (2) I use EBITDA in place of cash flow; (3) I use net assets as the denominator; (4) I include in fixed investment the estimated investment in operating leases

[38] Presumably, interactions between fixed capital, high-skill labor, and low-skill labor might have important implications for corporate policies. But a careful analysis will be needed to answer whether and how they do.

(the change in the capitalized value of total operating lease expenses).[39]

7. Conclusion

Starting from the notion of inventory as a factor of production rooted in the macroeconomics literature, this paper offers a novel insight on corporate investment policy and its cross-section. Using the data simulated from an investment model that incorporates fixed capital and inventory into firms' problem, I show that firm inventory dependence—firms' optimal behavior taking into account adjustment-cost difference and inventory-capital substitutability—renders fixed investment less responsive to variation in productivity. My empirical evidence lends strong support to this prediction. The response of fixed investment to firm profitability, industry-peer growth, and economic policy uncertainty among the group of low inventory-dependence firms is two to three times as strong as that of the group of high inventory-dependence firms. A mirror image of these results obtains for the response of inventory investment. Importantly, the effect of this real-side characteristic differs from that of financial constraints. The experiments exploiting industry-wide input-price indices and state-wide investment tax credits, respectively, provide further empirical support. An investigation from the allocation-of-funds perspective indicates that in response to a one-dollar increase in internal funds, a low (high) inventory-dependence firm allocates, on average, 15, 9 and 11 (7, 23 and 8) cents to fixed investment, inventory investment and acquisitions although the total allocation to these investing activities is similar across the two types of firms.

Discovering significant firm heterogeneity in inventory dependence and its impact goes a long way towards studying corporate investment in a variety of settings. For example, researchers concerned with evaluating the effect of a program on firms' investment can sharpen such an analysis by matching their sample on the inventory dependence measure proposed in this article. My evidence underscores the importance of bringing this real-side friction into the table.

[39] The estimation of the capitalized value of a firm's operating leases follows Eisfeldt and Rampini (2009). It is calculated as the present value of the perpetuity of the current operating lease expenses (*xrent*) using the discount rate of 10%. Then, the change in this value is added to fixed investment.

Appendix A Calibration and Numerical Procedure

Since the solutions to the model outlined in Section 3 are unavailable in a closed form, I solve the firm's problem numerically. The model is calibrated at quarterly frequency. Simulating shocks to firm productivity then yields the quarterly firm-level data and I transform these variables to annual ones to match the empirical data.

A.1 Calibration

Table A1 summarizes the parameters used in the calibration of my model. The parameter values are taken from the previous studies whenever appropriate. If they are not readily available from the literature, I pick the one that best replicates the relevant empirical moments.

The first set of parameters describes the firm productivity process. I set the persistence of productivity to be $\rho_x = 0.7^{1/4}$. While taken from Imrohoroglu and Tuzel's (2014) estimation, this is consistent with the one used in other studies (e.g., Zhang (2005) uses 0.97 ($= 0.7^{1/12}$) for the monthly frequency). Imrohoroglu and Tuzel estimate the cross-sectional standard deviation of the firm productivity to be approximately 0.4. Given this unconditional volatility and the annual persistence, the conditional volatility of the AR(1) process is calculated as $\sigma_x = 0.4\sqrt{1-0.7^2}\frac{1}{\sqrt{4}} = 0.29\frac{1}{\sqrt{4}}$.

The next set of parameters describes the production technologies. The depreciation rate of fixed capital is set to be $\delta_k = 0.12\frac{1}{4}$, roughly consistent with the values used in the extant studies (Kydland and Prescott, 1982; Zhang, 2005; Belo and Lin, 2012). The depreciation of inventory stock is viewed as non-interest inventory-carrying costs, including obsolescence and warehouse expenses. Industry experts estimate these costs to be 19% to 43% annually (Richardson, 1995). Therefore, I set $\delta_n = 0.24\frac{1}{4}$, also consistent with the values used by Belo and Lin (2012) and Jones and Tuzel (2013).

The degree of returns to scale is set to $\alpha = 0.7$, similar to the one used in, among others, Alti (2003), Cooper and Ejarque (2003) and Belo and Lin (2012). The fixed operating cost is assumed to be $f = 0.4\frac{1}{4}$. As Zhang (2005) notes, the fixed operating cost lowers the model-generated Q. The models without systematic risk, however, tend to overshoot this ratio unless the discount rate is unrealistically high.[40] Shutting down fixed operating cost does not affect my main conclusion.

The adjustment cost parameters are set to replicate the firm-level volatility of fixed investment

[40] For example, Alti (2003) reports an average Q of 2.5–5.8 from his model results. Belo and Lin (2012) note that setting $f = 0$ raises the market prices considerably, but has little impact on the real quantities in their model.

and that of inventory investment. However, these volatilities calculated from the simulated firms are expected to be lower than the ones observed in empirical data, again, due to the absence of aggregate shock in the model. The fixed-capital adjustment cost is set to $c_k = 8$ to generate a median volatility of fixed investment approximately 0.08. Similarly, inventory adjustment cost is set to $c_n = 2$ to generate a median volatility of inventory investment in the neighborhood of 0.15. The volatility of inventory investment is expected to increase in the ES (decrease in γ).

To demonstrate the impact of ES on investment policy, I experiment with different values of γ. As Kydland and Prescott (1982) note, ES > 1, although not impossible, is unlikely. So $\gamma = 0$, an assumption implicit in the Cobb-Douglas function, seems to be a reasonable lower bound. I experiment with three values, namely, $\gamma \in \{0.1, 1, 3\}$, which yield ES 0.91, 0.5 and 0.25, respectively. The effect of ES on firms' investment decision interacts with s_k, the relative weight on capital. A higher ES encourages inventory investment, and thus leads to a relatively large amount of inventory stock. Therefore, given a value of γ, I set s_k to generate a median inventory-to-capital ratio N/K in the neighborhood of 0.8, although I allow the medians to increase in ES. This is roughly consistent with the median observed in the U.S. manufacturing firm data. The approach is similar to the one employed by Jones and Tuzel (2013). Finally, the discount rate is set to $r = 0.05\frac{1}{4}$ to yield a discount factor of 0.99 quarterly.

A.2 Numerical Procedure

I use the value-function iteration method to solve the firm's problem. The value function and the optimal decision rules are solved on a grid in a discrete state space. For the construction of the grids for fixed capital K and inventory N, I use the recursive method of McGrattan (1999). That is, using the equation $K_j = K_{j-1} + c_1 \exp\left[c_2 (j-2)\right]$, where $j = 1, ..., n$ is the index of grid points, I choose two constants c_1 and c_2 to provide the desired number of grid points and the upper bound K_{max} given a pre-specified lower bound K_{min} (the same algorithm is applied to inventory N). The advantage of this recursive construction is that more grid points are assigned around the lower bound, where the value function has most of its curvature. I build a grid in which the number of points is 56 in each dimension, K and N, and upper bounds are large enough to be non-binding at all times. To transform the productivity state X into a discrete state space, I use a nine-state Markov process. The popular method of Tauchen and Hussey (1991) is known to work poorly when the persistence of AR(1) process is above 0.9 (Zhang, 2005). Because the persistence ρ_x exceeds 0.9 at quarterly frequency, I use the method described in Rouwenhorst

(1995) for a quadrature of the Gaussian shocks. Once the discrete state space is available, the conditional expectation operator in Equation (9) can be carried out as a matrix multiplication. The results are robust to the finer grids for the state variables.

For each set of parameters, I obtain solutions to the model and simulate 2000 firms over 1200 quarters (300 years), and drop the first 200 years to remove the effect of initial values of the state variables. This yields the data on firm values, fixed capital, inventory, investments in these factors, and operating profits. The quarterly variables are aggregated to an annual frequency to perform the analysis in Section 3.

Appendix B Variable Definitions

All raw data items are inflation-adjusted to 2008 dollars and the variables are winsorized at 1% in both tails. Variable definitions (Compustat/CRSP item names in parentheses when applicable) are as follows:

Fixed investment $I^K_{i,t}$	Capex minus sale of capital ($capx - sppe$) divided by the beginning-of-year assets (at) $A_{i,t-1}$.
Inventory investment $I^N_{i,t}$	Change in inventory ($invt_t - invt_{t-1}$) divided by $A_{i,t-1}$.
Input-inventory investment $I^{N^{inp}}_{i,t}$	Change in input inventory ($invrm_t + invwip_t - invrm_{t-1} - invwip_{t-1}$) divided by $A_{i,t-1}$.
$\sigma[X]$ ($mean[X]$)	The firm-level standard deviation (mean) of variable X calculated over past ten years. Non-missing data for at least five years are required.
Inventory dependence measure $\mathrm{NDEP}_{i,t}$	The standardized value of the first principal-component of $\sigma\left[I^N\right]$ and $mean\,[N/K]$.
Market to book $Q_{i,t-1}$	The ratio of market value to book value, where market value equals book value minus book common equity minus deferred tax and investment credit plus market equity ($at - ceq - txditc + prcc\_f \times csho$). If ceq is unavailable, book common equity is seq minus preferred stock, where preferred stock is $pstkrv$, $pstkl$ or $pstk$, in that order.
Excess return $R^{ex}_{i,t-1}$	Past 12-month stock return (ret) minus the CRSP value-weighted market return ($vwretd$), using monthly return series compounded.
$Leverage_{i,t-1}$	Total debt ($dltt + dlc$) divided by book assets, all measured at $t-1$.
$IndNAGR^{-i}_{i,j,t}$	Industry (two-digit SIC) mean net asset growth, where net asset growth is $\ln\left[NA_{i,t}/NA_{i,t-1}\right]$ and NA is total assets minus cash (che). The corresponding firm i itself is excluded from the calculation.
$IndSGR^{-i}_{i,j,t}$	Industry (two-digit SIC) mean sales growth, where sales growth is $\ln\left[sale_t/sale_{t-1}\right]$. The corresponding firm i itself is excluded from the calculation.

(*continued*)

$-\ln PU_t^{BBD}$	Baker et al.'s (2016) news-based political uncertainty index, logged and multiplied by minus one. PU_t^{BBD} is the one-quarter-lagged average of the index values from month $m-14$ through $m-3$, where m refers to each firm's fiscal-year-end month.
Input-price shock $Positive_{j,t}$ ($Negative_{j,t}$)	A dummy variable $Positive_{j,t}$ ($Negative_{j,t}$) equals one if a reduction in the BEA input-price index is above the top 30th percentile (below the bottom 30th percentile) for industry j.
Change in state investment tax credit $\Delta ITC_{s,t}$	A dummy variable $ITC\ incr_{s,t}$ ($ITC\ decr_{s,t}$) equals one if ITC has increased (decreased) in state s; $ITC\ incr \geq 1\%$ ($ITC\ decr \geq 1\%$) equals one if an increase (decrease) is 1% or larger; and ΔITC is the magnitude of change in ITC. The state ITC data (available up to 2006) come from Chirinko and Wilson (2008).
Cash flow $CF_{i,t}$	Net income plus depreciation ($ib + dp$) divided by $A_{i,t-1}$.
Net internal funds $CFADJ_{i,t}$	The sum of income before extraordinary items (ibc), depreciation (dpc), extra items and discontinued operations ($xidoc$), deferred taxes ($txdc$), equity in net loss ($esubc$), gains in sale of investment ($sppiv$) and other funds from operations ($fopo$), all divided by $A_{i,t-1}$.
$NetAcquisition_{i,t}$	Cash acquisition minus proceeds from the sale of investments in unconsolidated affiliates ($aqc - siv$) divided by $A_{i,t-1}$.
$\Delta ONWC_{i,t}$	Change in other NWC divided by $A_{i,t-1}$, where other NWC equals conventional NWC ($act - lct - che$) minus inventory ($invt$).
$\Delta Cash_{i,t}$	Change in cash and cash equivalents (che) divided by $A_{i,t-1}$.
$Div_{i,t}$	Total dividends (dvt) divided by $A_{i,t-1}$.
$EquityIssue_{i,t}$	Share issue minus repurchase ($sstk - prstkc$) divided by $A_{i,t-1}$.
$DebtIssue_{i,t}$	Long-term debt issue minus redemption ($dltis - dltr$) divided by $A_{i,t-1}$.
$\Delta STD_{i,t}$	Change in short-term debt (dlc) divided by $A_{i,t-1}$.
SA index	Hadlock and Pierce (2010). $SA\ index = -0.737Size + 0.043Size^2 - 0.04Age$, where $Size$ is the natural log of book assets (in 2008 dollars) and Age is the number of years a firm has appeared in Compustat. The book value and the number of years, respectively, are capped at \$4500 million and 37 years.
Altman's Z score	Altman (1968). $Z\ score = +1.2\frac{WC}{A} + 1.4\frac{RE}{A} + 3.3\frac{EBIT}{A} + 0.6\frac{ME}{BL} + 0.999\frac{Sales}{A}$, where WC is ($act - lct$), RE is retained earnings, $EBIT$ is $oiadp$, ME is market value of equity, and BL is total liabilities (lt).

References

[1] Abel, A.B., Eberly, J.C., 1994. A unified model of investment under uncertainty. *American Economic Review* 84, 1369–1384.

[2] Abel, A.B., Eberly, J.C., 2011. How Q and cash flow affect investment without frictions: An analytic explanation. *Review of Economic Studies* 78, 1179–1200.

[3] Almeida, H., Campello, M., Galvao, A.F., 2010. Measurement errors in investment equations. *Review of Financial Studies* 23, 3279–3328.

[4] Almeida, H., Hankins, K.W., Williams, R., 2017. Risk management with supply contracts. *Review of Financial Studies* 30, 4179–4215.

[5] Alti, A., 2003. How sensitive is investment to cash flow when financing is frictionless? *Journal of Finance* 58, 707–722.

[6] Altman, E.I., 1968. Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *Journal of Finance* 23, 589–609.

[7] Arellano, M., Bond, S., 1991. Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *Review of Economic Studies* 58, 277–297.

[8] Autor, D.H., Donohue, J.J., Schwab, S.J., 2006. The costs of wrongful-discharge laws. *Review of Economics and Statistics* 88, 211–231.

[9] Baker, S.R., Bloom, N., Davis, S.J., 2016. Measuring economic policy uncertainty *Quarterly Journal of Economics* 131, 1593–1636.

[10] Bates, T.W., Kahle, K.M., Stulz, R.M., 2009. Why do U.S. firms hold so much more cash than they used to? *Journal of Finance* 64, 1985–2021.

[11] Belo, F., Lin, X., 2012. The inventory growth spread. *Review of Financial Studies* 25, 278–313.

[12] Belo, F., Li, J., Lin, X., Zhao, X., 2017. Labor-force heterogeneity and asset prices: The importance of skilled labor, *Review of Financial Studies* 30, 3669–3709.

[13] Bertrand, M., Mullainathan, S., 2003. Enjoying the quiet life: Corporate governance and managerial preferences, *Journal of Political Economy* 111, 1043–1075.

[14] Blanchard, O.J., Lopezdesilanes, F., Shleifer, A., 1994. What do firms do with cash windfalls? *Journal of Financial Economics* 36, 337–360.

[15] Blatter, M., Muehlemann, S., Schenker, S., 2012. The costs of hiring skilled workers, *European Economic Review*, 56, 20–35.

[16] Blinder, A.S., Maccini, L.J., 1991. Taking stock: A critical assessment of recent research on inventories. *Journal of Economic Perspectives* 5, 73–96.

[17] Chang, X., Dasgupta, S., Wong, G., Yao, J., 2014. Cash flow sensitivities and the allocation of internal cash flow. *Review of Financial Studies* 27, 3628–3657.

[18] Chen, H., Chen, S., 2012. Investment-cash flow sensitivity cannot be a good measure of financial constraints: Evidence from the time series. *Journal of Financial Economics* 103, 393–410.

[19] Chirinko, R.,Wilson, D., 2008. State investment tax incentives: A zero-sum game? *Journal of Public Economics* 92, 2362–2384.

[20] Christiano, L.J., 1988. Why does inventory investment fluctuate so much? *Journal of Monetary Economics* 21, 247–280.

[21] Christiano, L.J., Eichenbaumab, M. 1987. Temporal aggregation and structural inference in macroeconomics, Carnegie-Rochester Conference Series on Public Policy 26, 63–130.

[22] Cleary, S., 1999. The relationship between firm investment and financial status. *Journal of Finance* 54, 673–692.

[23] Cooper, R., Ejarque, J., 2003. Financial frictions and investment: Requiem in Q. *Review of Economic Dynamics* 6, 710-728.

[24] Dasgupta, S., Li, E.X., Yan, D., 2018. Inventory behavior and financial constraints: Theory and evidence. *Review of Financial Studies* (forthcoming).

[25] Dixit, Avinash K., Pindyck, Robert S., 1994. Investment under uncertainty, Princeton University Press, Princeton, NJ.

[26] Eisfeldt, A.L., Rampini, A.A., 2009. Leasing, ability to repossess, and debt capacity. *Review of Financial Studies* 22, 1621–1657.

[27] Erickson, T., Jiang, C.H., Whited, T.M., 2014. Minimum distance estimation of the errors-in-variables model using linear cumulant equations. *Journal of Econometrics* 183, 211–221.

[28] Erickson, T., Whited, T.M., 2000. Measurement error and the relationship between investment and Q. *Journal of Political Economy* 108, 1027–1057.

[29] Erickson, T., Whited, T.M., 2012. Treating measurement error in Tobin's Q. *Review of Financial Studies* 25, 1286–1329.

[30] Fazzari, S.M., Hubbard, R.G., Petersen, B.C., 1988. Financing constraints and corporate investment. *Brookings Papers on Economic Activity* 19, 141–195.

[31] Feldstein, M.S., Auerbach, A.J., 1976. Inventory behavior in durable goods manufacturing: The target adjustment model. *Brookings Papers on Economic Activity* 7, 351–396.

[32] Gala, V.D., Gomes, J.F., 2016. Investment without Q. Unpublished working paper. University of Pennsylvania.

[33] Gao, X., 2017. Corporate cash hoarding: The role of just-in-time adoption. *Management Science* 64, 4858–4876.

[34] Gatchev, V., Pulvino, T., Tarhan, V., 2010. The interdependent and intertemporal nature of financial decisions: An application to cash flow sensitivities. *Journal of Finance* 65, 725–763.

[35] Gomes, J.F., 2001. Financing investment. *American Economic Review* 91, 1263–1285.

[36] Gulen, H., Ion, M., 2016. Policy uncertainty and corporate investment. *Review of Financial Studies* 29, 523–564.

[37] Hadlock, C.J., Pierce, J.R., 2010. New evidence on measuring financial constraints: Moving beyond the KZ Index. *Review of Financial Studies* 23, 1909–1940.

[38] Hayashi, F., 1982. Tobin's marginal Q and average Q: A neoclassical interpretation. *Econometrica* 50, 213–224.

[39] Hendricks, K.B., Singhal V.R., 2003. The effect of supply chain glitches on shareholder wealth. *Journal of Operations Management* 21, 501–522.

[40] Hubbard, R.G., 1998. Capital-market imperfections and investment. *Journal of Economic Literature* 36, 193–225.

[41] Imrohoroglu, A., Tuzel, S., 2014. Firm-level productivity, risk, and return. *Management Science* 60, 2073–2090.

[42] Jens, C.E., 2017. Political uncertainty and investment: Causal evidence from U.S. gubernatorial elec-tions. *Journal of Financial Economics* 124, 563–579.

[43] Jones, C.S., Tuzel, S., 2013. Inventory investment and the cost of capital. *Journal of Financial Economics* 107, 557–579.

[44] Julio, B., Yook, Y., 2012. Political uncertainty and corporate investment cycles. *Journal of Finance* 67, 45–84.

[45] Kaplan, S.N., Zingales, L., 1997. Do investment-cash flow sensitivities provide useful measures of financing constraints? *Quarterly Journal of Economics* 112, 169–215.

[46] Khan, A., Thomas, J.K., 2007. Inventories and the business cycle: An equilibrium analysis of (S,s) policies. *American Economic Review* 97, 1165–1188.

[47] Kydland, F.E., Prescott, E.C., 1982. Time to build and aggregate fluctuations. *Econometrica* 50, 1345–1370.

[48] Lamont, O., Polk, C., Saa-Requejo, J., 2001. Financial constraints and stock returns. *Review of Financial Studies* 14, 529-554.

[49] Lewellen, J., Lewellen, K., 2016. Investment and cash flow: New evidence. *Journal of Financial and Quantitative Analysis*, 51, 1135–1164.

[50] Lieberman, M.B., and Demeester, L., 1999. Inventory reduction and productivity growth: Linkages in the Japanese automotive industry. *Management Science* 45, 466–485.

[51] McGrattan, E.R., 1999. Application of weighted residual methods to dynamic economic models. In: Marimon, R., Scott, A. (Eds.), *Computational Methods for the Study of Dynamic Economies*. Oxford University Press, Oxford, UK.

[52] Montgomery, M.R., 1995. Time-to-build completion patterns for nonresidential structures, 1961–1991. *Economic Letters* 48, 155-163.

[53] Poterba, J.M., 1988. Financing constraints and corporate investment: Comment. *Brookings Papers on Economic Activity* 19, 200–204.

[54] Ramey, V.A., 1989. Inventories as factors of production and economic fluctuations. *American Economic Review* 79, 338–354.

[55] Ramey, V.A., West, K.D., 1999. Inventories. In: Taylor, J.B., Woodford, M. (Eds.), *Handbook of Macroeconomics*, vol. 1, Elsevier, Amsterdam, pp.863–923.

[56] Rauh, J.D., 2006. Investment and financing constraints: Evidence from the funding of corporate pension plans. *Journal of Finance* 61, 33–71.

[57] Richardson, H., 1995. Control your costs—then cut them. *Transportation and Distribution* (December), pp.94–96.

[58] Roodman, D.M., 2009. A note on the theme of too many instruments. *Oxford Bulletin of Economics and Statistics* 71, 135–158.

[59] Rouwenhorst, K.G., 1995. Asset pricing implications of equilibrium business cycle models. In: Cooley, T.F. (Ed.), *Frontiers of Business Cycle Research*. Princeton University Press, Princeton, NJ, pp.294–330.

[60] Rumyantsev, S., Netessine, S., 2007. What can be learned from classical inventory models? A cross-industry exploratory investigation. *Manufacturing & Service Operations Management* 9, 409–429.

[61] Stein, J.C., 2003. Agency information and corporate investment. In: Constantinides, G., Harris, M., Stulz, R. (Eds.), *Handbook of the Economics of Finance* vol. 1a, Elsevier, Amsterdam, pp.111–165.

[62] Tauchen, J., Hussey, R., 1991. Quadrature-based methods for obtaining approximate solutions to nonlinear asset pricing models. *Econometrica* 59, 371–396.

[63] Tsoukalas, J.D., 2011. Time to build capital: Revisiting investment-cash-flow sensitivities. *Journal of Economic Dynamics and Control* 35, 1000–1016.

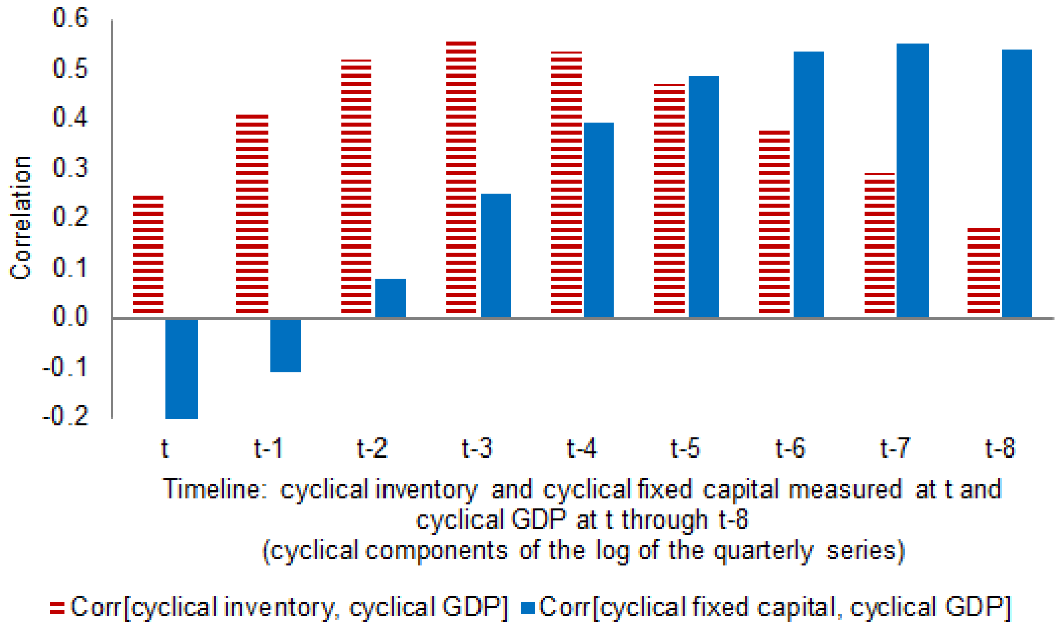
[64] Zhang, L., 2005. The value premium. *Journal of Finance* 60, 67–103.

[65] Zipkin, P.H., 1991. Does manufacturing need a JIT revolution? *Harvard Business Review* 69, 40–50.

Figure 1: Lead-lag patterns of aggregate investments

Panel A reports correlations of the cyclical components of inventory and fixed capital, respectively, with the cyclical component of real GDP, and Panel B the cross-correlation between fixed-capital growth and inventory growth. The sample period spans 1970:Q1−2015:Q4. Data on the replacement-cost values of fixed capital (the sum of equipment and nonresidential structures) and inventory are from the Federal Reserve Statistical Release Z.1, Table B.103 Balance Sheet of Nonfinancial Corporate Business. To obtain the cyclical components used in Panel A, the raw data series have been logged and detrended using the Hodrick-Prescott filter ($\lambda = 1,600$). The quarterly growth rates used in Panel B are log-changes in the raw data series.

Panel A: Correlations of inventory and fixed capital with GDP (cyclical components)



Panel B: Cross-correlation between inventory growth and fixed-capital growth

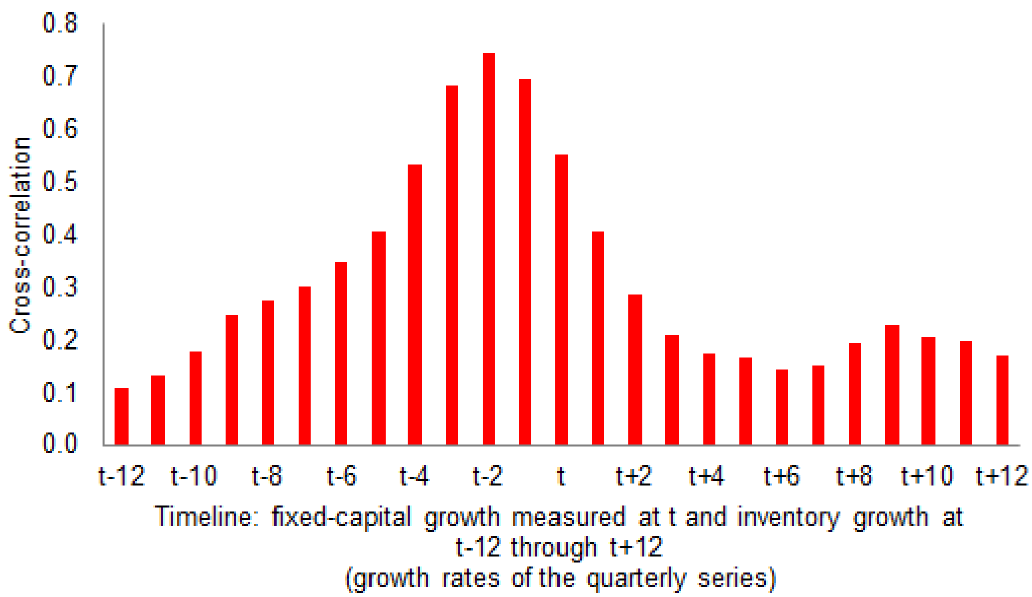


Figure 2: Within-firm variation in inventory investment by industry

Plots the within-firm 10th, 50th, and 90th percentiles of inventory investment to lagged assets for each industry. The within-firm percentiles are calculated for each firm with at least seven years of valid data between 1970 and 2015; these percentiles are then averaged for each industry based on two-digit SIC codes, as displayed at the bottom of the figure. Tobacco industry (SIC 2100−2199) is not displayed. The sample consists of the U.S. manufacturing firms.

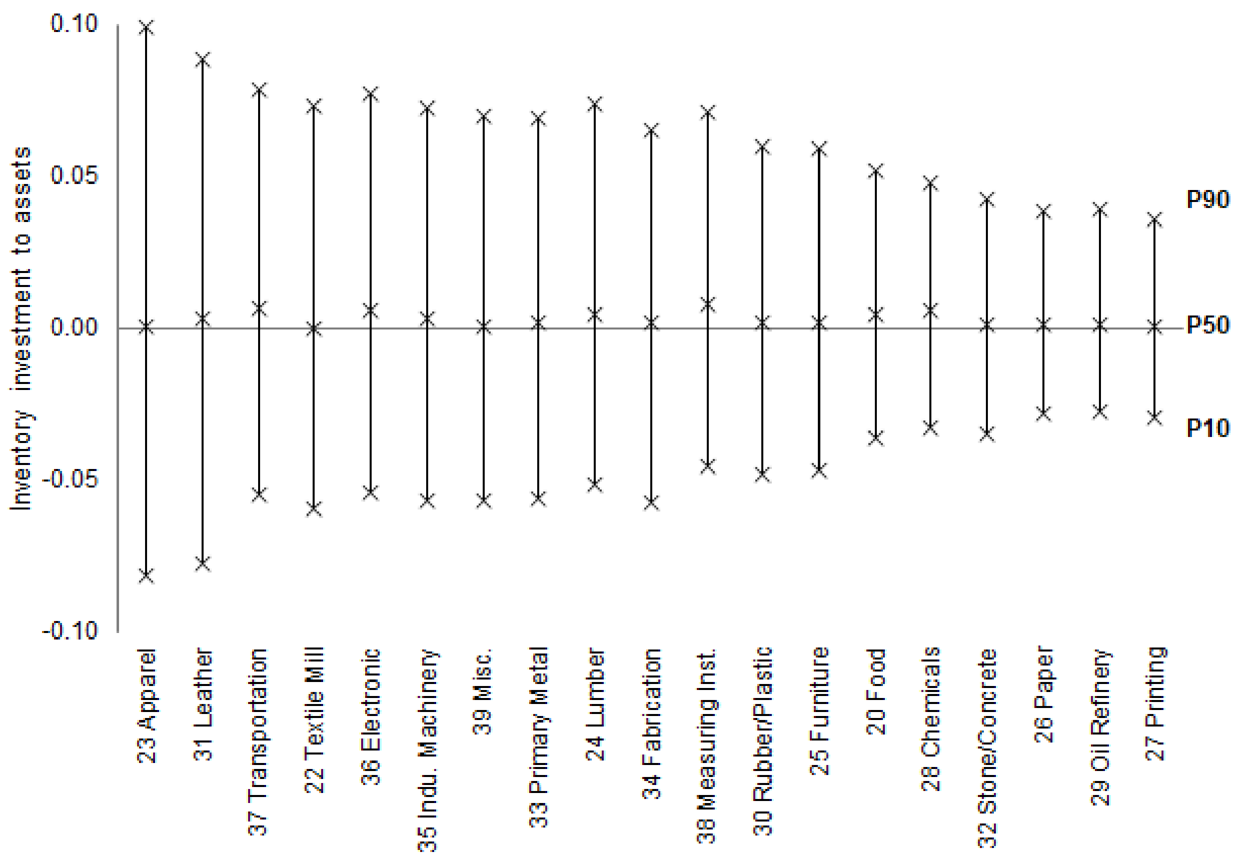


Figure 3: Within-firm variation in inventory investment and fixed investment
Plots the within-firm 10th, 50th, and 90th percentiles of inventory investment and fixed investment, both scaled by the lagged assets. The within-firm percentiles are calculated for each firm with at least seven years of valid data between 1970 and 2015; these percentiles are then averaged for the low and the high inventory dependence (NDEP) subsamples. The sample consists of the U.S. manufacturing firms. Section 4 describes in detail the data and the sample sorting and matching procedures.

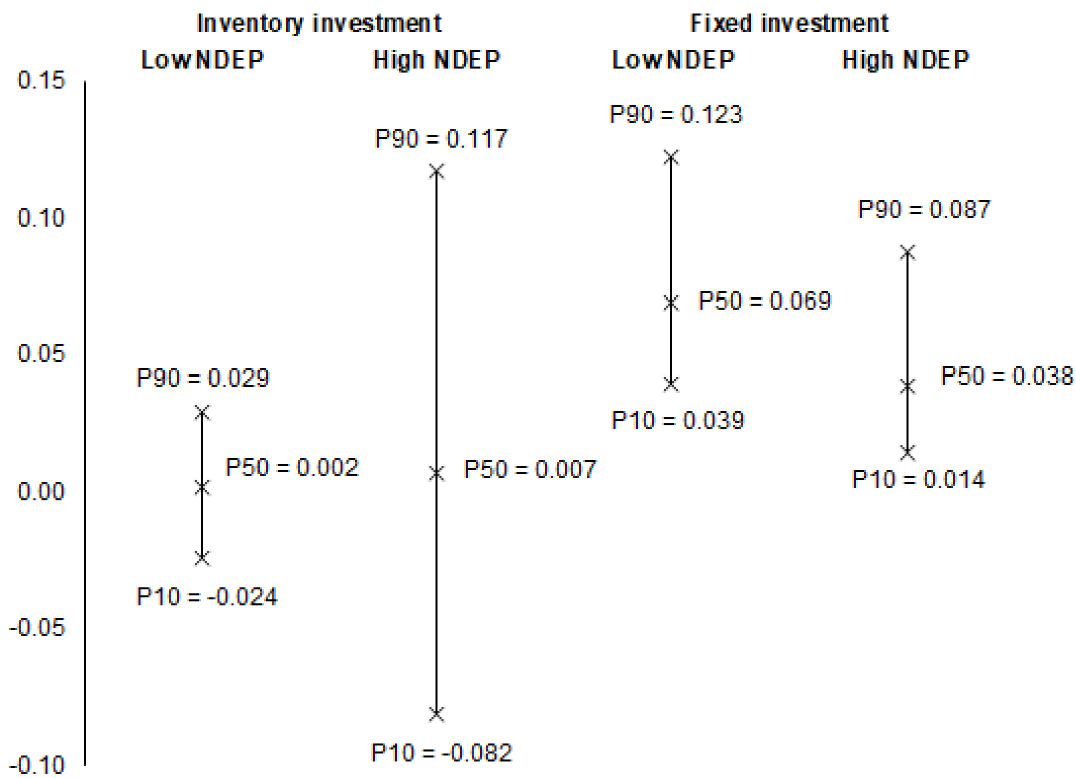


Figure 4: Within-firm correlations of investments with real GDP (cyclical components)

Plots the within-firm correlations of cyclical inventory and cyclical fixed capital, respectively, with cyclical real GDP, all measured at the quarterly frequency. The sample consists of the U.S. manufacturing firms that have positive values for inventory (*invtq*) and fixed capital (*ppentq*) from the Compustat quarterly tape. The quarterly items *invtq* and *ppentq* are available from 1976 onwards. To obtain the cyclical component of GDP, the raw data series have been logged and detrended using the Hodrick-Prescott filter ($\lambda = 1,600$). By applying the same procedure, the cyclical components of inventory and fixed capital are calculated for each firm with at least 30 quarters of valid data between 1976 and 2015. The within-firm correlation between cyclical inventory and cyclical GDP and that between cyclical fixed capital and cyclical GDP, respectively, are then calculated for each firm with at least 30 quarters of valid data. The medians of these correlations are reported for the low and high inventory dependence (NDEP) subsamples. Section 4 describes in detail the data and the sample sorting and matching procedures.

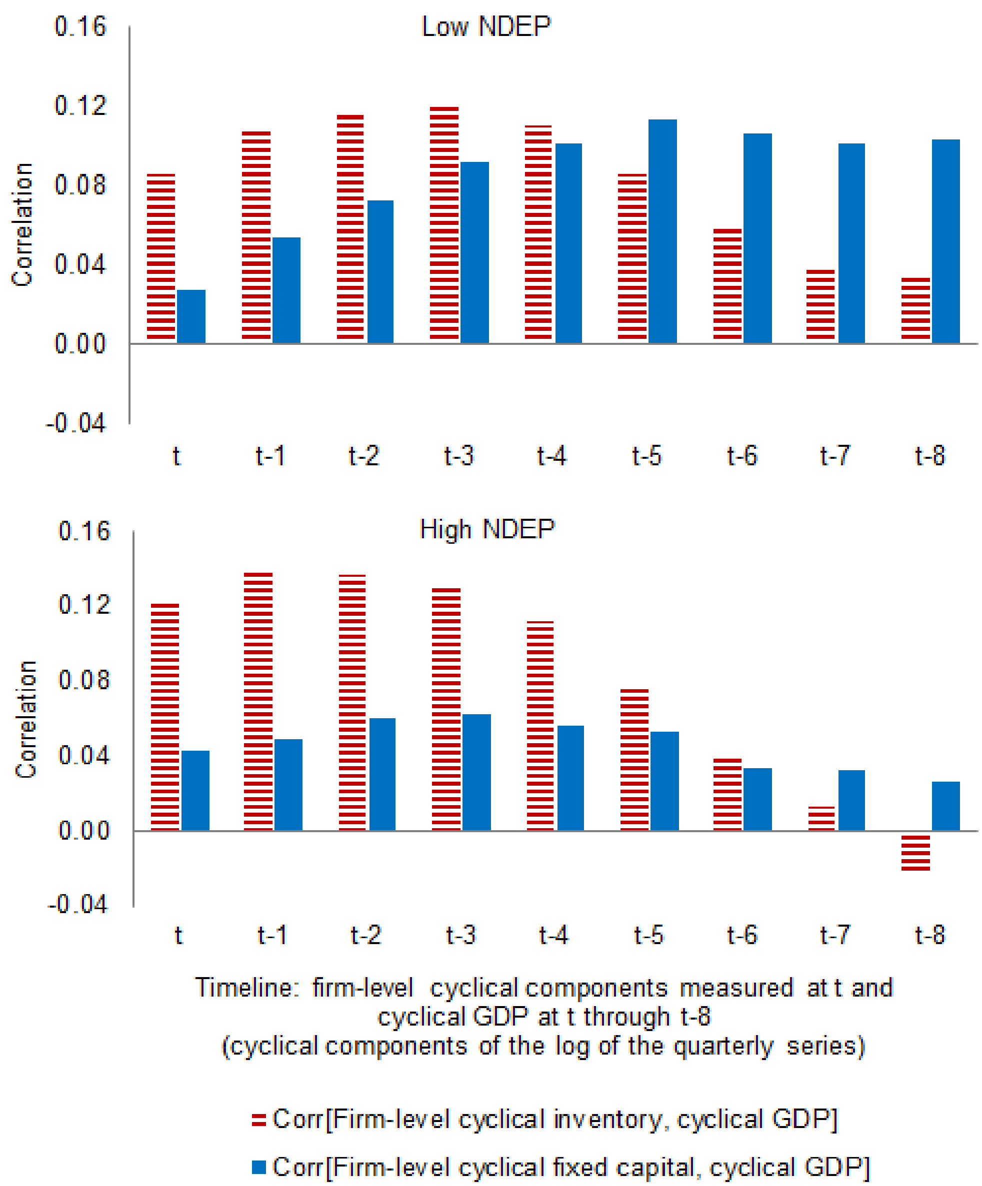


Figure 5: Industry-level evidence

Plots the industry-level responses of fixed investment to firm profitability against the industry means of the inventory-dependence measure (NDEP). The estimates are the sum of λ_1 and λ_2 from $I^K_{i,t} = \lambda_1 x_{i,t} + \lambda_2 x_{i,t-1} + \Psi z_{i,t} + a_i + b_t + \varepsilon_{i,t}$, where $I^K_{i,t}$ is fixed investment and $x_{i,t}$ is cash flow, all scaled by the lagged assets $A_{i,t-1}$. The vector $z_{i,t}$ includes $Q_{i,t-1}$, $R^{ex}_{i,t-1}$, $\ln A_{i,t-1}$ and $Leverage_{i,t-1}$. a_i and b_t, respectively, are firm and year fixed effects. The sample consists of the U.S. manufacturing firms from 1980−2015. Industry classification is based on two-digit SIC codes, as indicated next to the abbreviated industry names. Tobacco industry (SIC 2100−2199) is not displayed. Section 4 describes in detail the data and the NDEP measure.

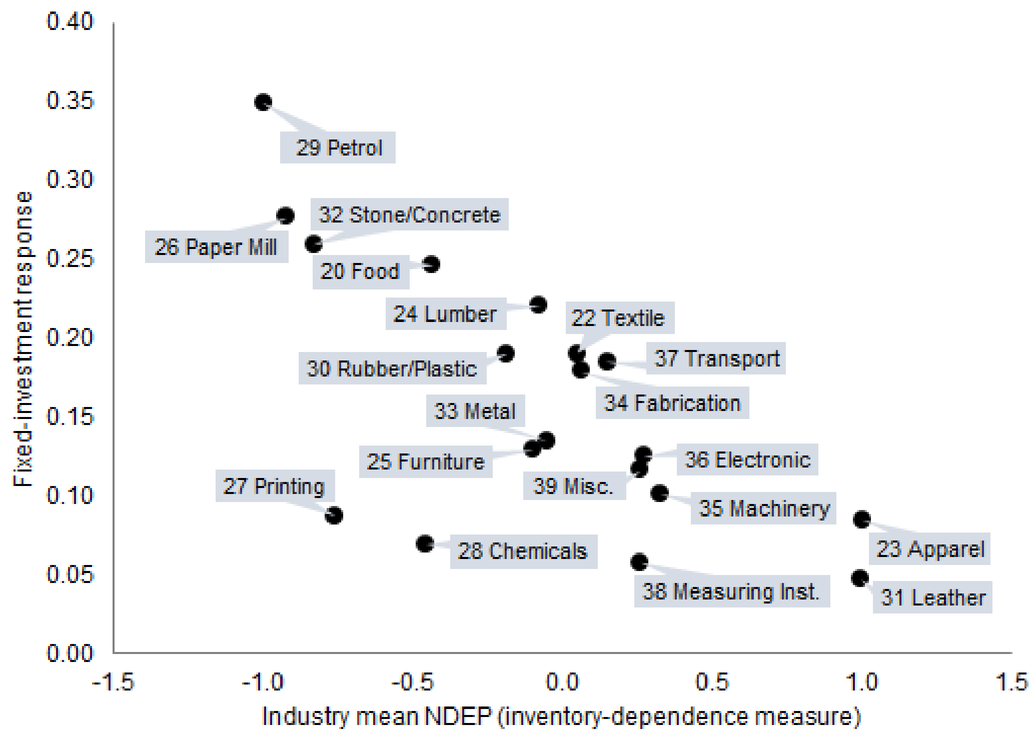
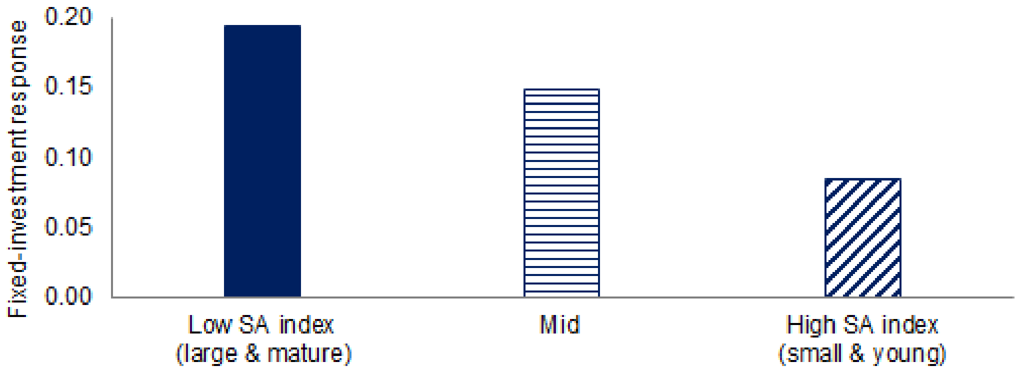


Figure 6: Investment-profitability relationship across the size-and-age subsamples
Panel A reports the responses of fixed investment to firm profitability for the one-way-sorted subsamples based on the SA-index terciles. Panel B reports the results for the dependent-two-way-sorted subsamples based on the SA-index terciles, generated within each NDEP decile. The estimates are the sum of λ_1 and λ_2 from $I^K_{i,t} = \lambda_1 x_{i,t} + \lambda_2 x_{i,t-1} + \Psi z_{i,t} + a_i + b_t + \varepsilon_{i,t}$, where $I^K_{i,t}$ is fixed investment and $x_{i,t}$ is cash flow, all scaled by the lagged assets $A_{i,t-1}$. The vector $z_{i,t}$ includes $Q_{i,t-1}$, $R^{ex}_{i,t-1}$, $\ln A_{i,t-1}$ and $Leverage_{i,t-1}$. a_i and b_t, respectively, are firm and year fixed effects. The sample consists of the U.S. manufacturing firms from 1980−2015. Section 4 describes in detail the data and the sample sorting and matching procedures.

Panel A: SA-index terciles without pre-sorting



Panel B: SA-index terciles generated within each NDEP decile

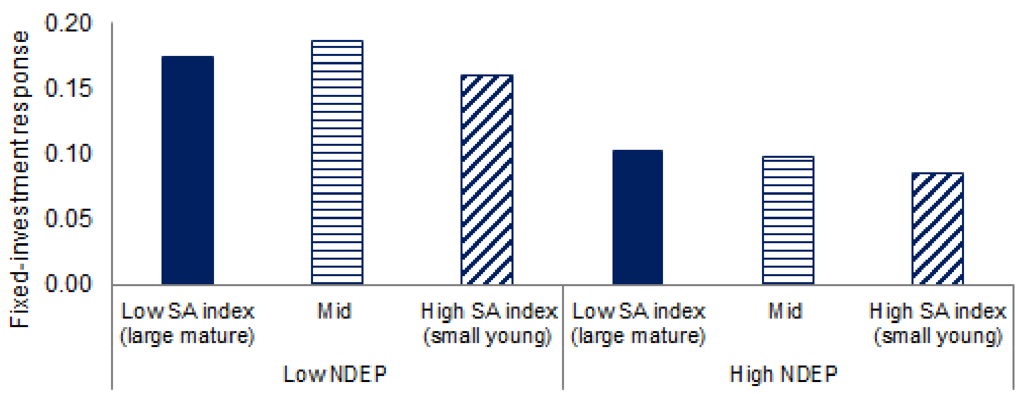


Table 1: Simulation results

Panel A reports the medians of variables generated from the model, and Panel B the estimation results of Equation (12). Each regression includes firm fixed effects. The data are simulated from the model with different values of ES as displayed in the column headers. $I^K_{i,t}$ is fixed investment, $I^N_{i,t}$ is inventory investment, and $\Pi_{i,t}$ is operating profits defined in Equation (1) in Section 3, all scaled by the lagged book assets. $\sigma[X]$ denotes the firm-level volatility of the variable X. Standard errors clustered at the firm level are reported. All estimated coefficients are significant at the 1% level.

	(1)	(2)	(3)
	Data from the model simulations		
	ES = 0.25 ($\gamma = 3$)	ES = 0.5 ($\gamma = 1$)	ES = 0.91 ($\gamma = 0.1$)
Panel A: Medians for the selected variables			
$\sigma\left[I^N\right]$	0.121	0.143	0.168
$\sigma\left[I^K\right]$	0.085	0.083	0.080
$(N/K)_{i,t}$	0.704	0.765	0.882
$I^K_{i,t}$	0.073	0.068	0.064
$\Pi_{i,t}$	0.313	0.311	0.312
$Q_{i,t-1}$	2.341	2.275	2.288
Panel B: Investment regression results			
Dependent var : $I^K_{i,t}$			
$\Pi_{i,t}$	**0.184**	**0.157**	**0.111**
	0.001	0.001	0.001
$Q_{i,t-1}$	0.044	0.043	0.040
	0.000	0.000	0.000
R^2	0.604	0.568	0.509
N	200,000	200,000	200,000

Table 2: Summary statistics

Columns 1−4 report the mean and the 25th, 50th, and 75th percentiles of the variables for the whole sample, and Columns 5 and 6 the medians for the low and high inventory-dependence groups. The sample consists of the U.S. manufacturing firms from 1980−2015. The subsamples in Column 5 are formed based on the NDEP terciles. In Column 6, the dependent two-way-sorted subsamples are formed based on the NDEP terciles, generated within each SA-index decile. Section 4 describes in detail the data and the sample sorting and matching procedures. $I^K_{i,t}$ is fixed investment, $I^N_{i,t}$ is inventory investment, $I^{N^{inp}}_{i,t}$ is input-inventory investment, and $CF_{i,t}$ is cash flow, all scaled by the lagged assets $A_{i,t-1}$. $IndNAGR^{-i}_{i,j,t}$ is industry-peer net asset growth, $IndSGR^{-i}_{i,j,t}$ is industry-peer sales growth, *Employment* is the number of employees, and *Years listed* is the number of years listed on the exchange. $\sigma[X]$ denotes the firm-level volatility of the variable X. See Appendix B for variable definitions in detail.

	(1)	(2)	(3)	(4)	(5a)	(5b)	(6a)	(6b)
					Medians for the subsamples			
	Whole sample				One-way-sort on NDEP		Dependent two-way-sort on SA index & NDEP	
	Mean	25 P	Median	75 P	Low	High	Low	High
NDEP, standardized	-0.001	-0.666	-0.022	0.663	-0.944	0.957	-0.863	0.943
$I^N_{i,t}$	0.003	-0.018	0.001	0.022	0.001	0.000	0.001	-0.001
$I^{N^{inp}}_{i,t}$	0.002	-0.012	0.000	0.013	0.000	0.000	0.000	0.000
$I^K_{i,t}$	0.052	0.021	0.040	0.069	0.051	0.030	0.050	0.031
$\sigma\left[I^N\right]$	0.048	0.024	0.040	0.064	0.019	0.077	0.021	0.072
$\sigma\left[I^{N^{inp}}\right]$	0.034	0.015	0.027	0.046	0.012	0.051	0.015	0.046
$\sigma\left[I^K\right]$	0.034	0.015	0.025	0.043	0.026	0.025	0.030	0.022
$(N/K)_{i,t}$	1.241	0.405	0.770	1.389	0.351	1.609	0.369	1.449
$\left(N^{inp}/K\right)_{i,t}$	0.720	0.225	0.450	0.861	0.205	0.889	0.226	0.802
$Q_{i,t-1}$	1.585	0.991	1.280	1.804	1.358	1.185	1.345	1.204
$CF_{i,t}$	0.085	0.050	0.094	0.137	0.106	0.075	0.106	0.079
$IndNAGR^{-i}_{i,j,t}$	0.048	0.011	0.050	0.092	0.050	0.050	0.050	0.050
$IndSGR^{-i}_{i,j,t}$	0.042	0.004	0.048	0.091	0.047	0.049	0.047	0.048
$Cash_{i,t-1}$	0.134	0.024	0.074	0.189	0.072	0.075	0.083	0.065
$Leverage_{i,t-1}$	0.202	0.064	0.191	0.304	0.210	0.170	0.193	0.193
$R\&D_{i,t-1}$	0.038	0.000	0.017	0.053	0.014	0.019	0.014	0.016
$\sigma\left[CF\right]$	0.058	0.027	0.043	0.073	0.034	0.058	0.039	0.051
$Employment_{i,t}/A_{i,t}$ ($\times$100 thousand)	0.66	0.32	0.55	0.86	0.43	0.62	0.48	0.60
$\ln A_{i,t-1}$ (in \$2008, in mln.)	6.0	4.5	5.8	7.3	7.0	4.8	6.1	5.6
Years listed	25	13	20	32	24	17	19	22
SA index	-3.7	-4.3	-3.7	-3.2	-4.1	-3.4	-3.7	-3.7
Altman's Z score	4.5	2.6	3.6	5.2	3.4	3.7	3.6	3.6

Table 3: Impact of inventory dependence on investment responses

Reports the estimation results of Equations (13) and (14), where the dependent variables are fixed investment and inventory investment, scaled by the lagged assets $A_{i,t-1}$. The sample consists of the U.S. manufacturing firms from 1980−2015. The low and high inventory-dependence groups are formed based on the NDEP terciles. $x_{i,t}$ is either cash flow to assets (Columns 1 and 2), industry net asset growth (Column 3), or industry sales growth (Column 4). Each regression includes year and firm fixed effects. Section 4 describes in detail the data and the sample sorting and matching procedures. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively, based on standard errors clustered at the firm level.

	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)
	One-way-sorted on NDEP							
	Inventory dependence		Inventory dependence		Inventory dependence		Inventory dependence	
	Low	High	Low	High	Low	High	Low	High
	$x_{i,t} = CF_{i,t}$		$x_{i,t} = CF_{i,t}$		$x_{i,t} = IndNAGR^{-i}_{i,j,t}$		$x_{i,t} = IndSGR^{-i}_{i,j,t}$	
Panel A: Fixed investment								
sum $[x_{i,t},\ x_{i,t-1}]$			**0.200*****	**0.082*****	**0.120*****	**0.050*****	**0.074*****	**0.034*****
			(*diff. p value* = .00)		(*diff. p value* = .00)		(*diff. p value* = .01)	
$x_{i,t}$	**0.128*****	**0.058*****	0.084***	0.037***	0.051***	0.024***	0.024***	0.010
	(*diff. p value* = .00)		0.010	0.005	0.011	0.009	0.008	0.008
$x_{i,t-1}$			0.116***	0.045***	0.069***	0.026***	0.050***	0.024***
			0.012	0.006	0.010	0.010	0.008	0.008
$Q_{i,t-1}$	0.009***	0.010***	0.003***	0.007***	0.008***	0.009***	0.009***	0.009***
	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
$R^{ex}_{i,t-1}$			0.005***	0.002***	0.008***	0.004***	0.008***	0.004***
			0.001	0.001	0.001	0.001	0.001	0.001
$\ln A_{i,t-1}$			-0.010***	-0.003*	-0.010***	-0.002	-0.010***	-0.002
			0.002	0.001	0.002	0.001	0.002	0.001
$Leverage_{i,t-1}$			-0.048***	-0.045***	-0.069***	-0.058***	-0.071***	-0.059***
			0.007	0.006	0.008	0.006	0.008	0.006
R^2 (*within*)	0.078	0.065	0.135	0.103	0.098	0.084	0.093	0.084
Panel B: Inventory investment								
sum $[x_{i,t},\ x_{i,t-1}]$			**0.078*****	**0.226*****	**0.080*****	**0.184*****	**0.039*****	**0.090*****
			(*diff. p value* = .00)		(*diff. p value* = .00)		(*diff. p value* = .00)	
$x_{i,t}$	**0.073*****	**0.206*****	0.067***	0.182***	0.070***	0.189***	0.039***	0.101***
	(*diff. p value* = .00)		0.007	0.012	0.005	0.012	0.005	0.017
$x_{i,t-1}$			0.011***	0.044***	0.010**	-0.005	0.000	-0.011
			0.005	0.010	0.005	0.012	0.005	0.015
$Q_{i,t-1}$	0.002***	0.008***	0.000	0.001	0.002***	0.008***	0.002***	0.008***
	0.000	0.001	0.000	0.001	0.000	0.001	0.000	0.001
$R^{ex}_{i,t-1}$			0.003***	0.007***	0.004***	0.011***	0.004***	0.011***
			0.001	0.001	0.001	0.001	0.001	0.001
$\ln A_{i,t-1}$			-0.005***	-0.013***	-0.003***	-0.016***	-0.005***	-0.014***
			0.001	0.002	0.001	0.002	0.001	0.002
$Leverage_{i,t-1}$			-0.016***	-0.072***	-0.020***	-0.096***	-0.023***	-0.099***
			0.003	0.009	0.003	0.009	0.003	0.009
R^2 (*within*)	0.038	0.082	0.051	0.109	0.055	0.095	0.035	0.062
N	12,146	12,105	11,119	10,724	11,081	10,706	11,081	10,706

Table 4: Samples matched on financial constraints and other characteristics

Reports the estimation results of Equations (13) and (14), where the dependent variables are fixed investment and inventory investment, scaled by the lagged assets $A_{i,t-1}$. The sample consists of the U.S. manufacturing firms from 1980−2015. The two-way-sorted subsamples in Panel A (Panel B) are formed based on the NDEP terciles, generated within each SA-index decile (the credit-rating dummy). In Panel C, the sample is matched on the propensity score, based on two-digit SIC industry, fiscal year, the SA index, R&D intensity, $\sigma[Cashflow]$, $\ln A_{i,t-1}$, $Leverage_{i,t-1}$, and $Q_{i,t-1}$. Subpanel C3 reports differences in means between the score-matched subsamples. $x_{i,t}$ is either cash flow to assets (Columns 1 and 2), industry net asset growth (Column 3), or industry sales growth (Column 4). Each regression includes year and firm fixed effects, $Q_{i,t-1}$, $R^{ex}_{i,t-1}$, $\ln A_{i,t-1}$, and $Leverage_{i,t-1}$. Section 4 describes in detail the data and the sample sorting and matching procedures. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively, based on standard errors clustered at the firm level.

	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)
	Dependent-two-way-sorted or propensity-score-matched					
	Inventory dependence		Inventory dependence		Inventory dependence	
	Low	High	Low	High	Low	High
	$x_{i,t} = CF_{i,t}$		$x_{i,t} = IndNAGR^{-i}_{i,j,t}$		$x_{i,t} = IndSGR^{-i}_{i,j,t}$	
Panel A: Two-way-sorted (pre-sorted on the SA index)						
A1 Fixed investment						
sum $[x_{i,t},\ x_{i,t-1}]$	**0.184*****	**0.092*****	**0.124*****	**0.058*****	**0.076*****	**0.044*****
	(*diff. p value* = .00)		(*diff. p value* = .00)		(*diff. p value* = .03)	
A2 Inventory investment						
sum $[x_{i,t},\ x_{i,t-1}]$	**0.081*****	**0.234*****	**0.088*****	**0.175*****	**0.038*****	**0.092*****
	(*diff. p value* = .00)		(*diff. p value* = .00)		(*diff. p value* = .01)	
N	10,810	10,890	10,810	10,890	10,810	10,890
Panel B: Two-way-sorted (pre-sorted on credit rating)						
B1 Fixed investment						
sum $[x_{i,t},\ x_{i,t-1}]$	**0.163*****	**0.072*****	**0.090*****	**0.036*****	**0.050*****	**0.027*****
	(*diff. p value* = .00)		(*diff. p value* = .00)		(*diff. p value* = .09)	
B2 Inventory investment						
sum $[x_{i,t},\ x_{i,t-1}]$	**0.068*****	**0.209*****	**0.062*****	**0.160*****	**0.032*****	**0.086*****
	(*diff. p value* = .00)		(*diff. p value* = .00)		(*diff. p value* = .01)	
N	9,158	8,994	9,158	8,994	9,158	8,994
Panel C: Propensity-score-matched						
C1 Fixed investment						
sum $[x_{i,t},\ x_{i,t-1}]$	**0.200*****	**0.098*****	**0.120*****	**0.035***	**0.087*****	**0.018**
	(*diff. p value* = .00)		(*diff. p value* = .02)		(*diff. p value* = .02)	
C2 Inventory investment						
sum $[x_{i,t},\ x_{i,t-1}]$	**0.077*****	**0.238*****	**0.089*****	**0.203*****	**0.021***	**0.116*****
	(*diff. p value* = .00)		(*diff. p value* = .00)		(*diff. p value* = .01)	
N	4,301	4,301	4,301	4,301	4,301	4,301
C3 Differences in means for the score-matched subsamples						
	Low NDEP		High NDEP		**difference (*p value*)**	
SA index	-3.626		-3.636		**-0.010 (.40)**	
R&D	0.042		0.041		**-0.001 (.38)**	
Firm size (ln A)	5.746		5.777		**0.031 (.33)**	
Leverage	0.192		0.192		**0.000 (.94)**	
Q	1.566		1.572		**0.006 (.76)**	
$\sigma\,[Cashflow]$	0.068		0.068		**0.000 (.93)**	

Table 5: Economic policy uncertainty and investment responses

Reports the investment responses to the news-based political uncertainty index (Baker et al., 2016). The dependent variable is fixed investment or inventory investment, scaled by the lagged assets. The sample consists of the U.S. manufacturing firms from 1986−2015. The index values have been logged and multiplied by minus one so that higher values of $-\ln PU_t^{BBD}$ indicate *low* levels of uncertainty. Each regression includes firm fixed effects, $Q_{i,t-1}$, $R^{ex}_{i,t-1}$, $\ln A_{i,t-1}$, $Leverage_{i,t-1}$, $CF_{i,t}$, and GDP growth. Section 4 describes in detail the data and the sample sorting and matching procedures used to prepare the NDEP subsamples. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively, based on standard errors clustered at the firm level.

	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)
			Dependent two-way-sorted				Propensity-score-matched	
	One-way-sorted		Pre-sorted on SA index		Pre-sorted on rating			
	Inventory dependence		Inventory dependence		Inventory dependence		Inventory dependence	
	Low	High	Low	High	Low	High	Low	High
Panel A: Fixed investment								
$-\ln PU_t^{BBD}$	**0.013*****	**0.008*****	**0.013*****	**0.007*****	**0.014*****	**0.006*****	**0.013*****	**0.005***
	(*diff. p value* = .01)		(*diff. p value* = .00)		(*diff. p value* = .00)		(*diff. p value* = .04)	
R^2 (*within*)	0.158	0.092	0.134	0.112	0.140	0.105	0.131	0.110
Panel B: Inventory investment								
$-\ln PU_t^{BBD}$	**0.005*****	**0.019*****	**0.006*****	**0.015*****	**0.007*****	**0.015*****	**0.008*****	**0.021*****
	(*diff. p value* = .00)		(*diff. p value* = .00)		(*diff. p value* = .00)		(*diff. p value* = .00)	
R^2 (*within*)	0.059	0.122	0.056	0.130	0.055	0.123	0.071	0.113
N	9,713	9,672	9,716	9,603	9,700	9,668	3,736	3,736

Table 6: Input price shocks to inventory investment

Reports the investment responses to input price shocks. The industry-level indices for intermediate input prices are from the Bureau of Economic Analysis (BEA). $Positive_{j,t}$ ($Negative_{j,t}$) is a dummy variable that equals one if a reduction in the BEA input-price index at time t is above the top 30th percentile (below the bottom 30th percentile) for each industry j. The dependent variable is fixed investment or inventory investment, scaled by the lagged assets. The sample consists of the U.S. manufacturing firms from 1980−2015. Each regression includes firm fixed effects, industry-year fixed effects (the interaction of Fama-French 48 industry and year dummies), $Q_{i,t-1}$, $R^{ex}_{i,t-1}$, $\ln A_{i,t-1}$, $Leverage_{i,t-1}$, and $CF_{i,t}$. Section 4 describes in detail the data and the sample sorting and matching procedures used to prepare the NDEP subsamples. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively, based on standard errors clustered at the firm level.

	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)
			Dependent two-way-sorted				Propensity-	
	One-way-sorted		Pre-sorted on SA index		Pre-sorted on rating		score-matched	
	Inventory dependence		Inventory dependence		Inventory dependence		Inventory dependence	
	Low	High	Low	High	Low	High	Low	High
Panel A: Fixed investment								
$Positive_{j,t}$	0.001	0.004	0.000	0.003*	0.001	0.002	-0.003	0.002
	(*diff. p value* = .37)		(*diff. p value* = .38)		(*diff. p value* = .85)		(*diff. p value* = .25)	
$Negative_{j,t}$	0.003	0.000	0.004	-0.001	0.005*	-0.001	0.004	-0.002
	(*diff. p value* = .52)		(*diff. p value* = .32)		(*diff. p value* = .21)		(*diff. p value* = .31)	
R^2 (*within*)	0.092	0.083	0.085	0.099	0.082	0.086	0.107	0.085
Panel B: Inventory investment								
$Positive_{j,t}$	**0.001**	**0.010*****	**-0.001**	**0.008****	**0.002**	**0.010*****	**0.002**	**0.017*****
	(*diff. p value* = .03)		(*diff. p value* = .02)		(*diff. p value* = .03)		(*diff. p value* = .04)	
$Negative_{j,t}$	**-0.003***	**-0.010****	**-0.001**	**-0.011*****	**-0.003**	**-0.011*****	**-0.001**	**-0.002****
	(*diff. p value* = .07)		(*diff. p value* = .01)		(*diff. p value* = .04)		(*diff. p value* = .13)	
R^2 (*within*)	0.042	0.104	0.044	0.112	0.038	0.095	0.047	0.089
N	11,401	11,124	11,388	11,001	9,556	9,289	4,245	4,245

Table 7: State investment tax credits and fixed investment

Reports the investment responses to changes in investment tax credit (ITC). Change in ITC is measured as follows: $ITC\ incr_{s,t}$ ($ITC\ decr_{s,t}$) equals one if ITC has increased (decreased) in state s; $ITC\ incr \geq 1\%$ ($ITC\ decr \geq 1\%$) equals one if an increase (decrease) is 1% or larger; and ΔITC is change in ITC. The four dummy variables used for the pre-trend tests are as follows: 1 *year before* (0 *year before*) equals one if the state is about to have an ITC increase in one year (in the current year); and 1 *year after* (2/3 *years after*) equals one if it had an ITC increase one year ago (two or three years ago). The dependent variable is change in fixed investment $\Delta I^K_{i,t}$ or change in inventory investment $\Delta I^N_{i,t}$, scaled by the lagged assets. The sample consists of the U.S. manufacturing firms from 1980−2006. Each regression includes year and firm fixed effects, state unemployment rate, state real GDP growth, $\Delta Q_{i,t}$, $R^{ex}_{i,t-1}$, $\Delta \ln A_{i,t}$, $\Delta Leverage_{i,t}$, and $\Delta CF_{i,t}$. Section 4 describes in detail the data and the sample sorting and matching procedures used to prepare the NDEP subsamples. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively, based on standard errors clustered at the state level.

	(1)	(2)	(3)	(4)
	ITC incr/decr	*ITC incr/decr* $\geq 1\%$	ΔITC (continuous)	Pre-trend
Panel A: Whole sample diff-in-diff				
A1 Change in fixed investment				
$ITC\ increase_{s,t}$	**0.005****	**0.006*****		
	0.002	0.002		
$ITC\ decrease_{s,t}$	0.001	0.001		
	0.003	0.003		
$\Delta ITC_{s,t}$			**0.103***	
			0.055	
1 *year before*				-0.003
				0.002
0 *year before*				0.001
				0.002
1 *year after*				**0.005*****
				0.002
2/3 *years after*				0.001
				0.002
R^2	0.079	0.079	0.079	0.080
A2 Change in inventory investment				
$ITC\ increase_{s,t}$	0.000	0.002		
	0.004	0.004		
$ITC\ decrease_{s,t}$	-0.002	0.000		
	0.003	0.003		
$\Delta ITC_{s,t}$			-0.039	
			0.093	
1 *year before*				0.000
				0.003
0 *year before*				-0.001
				0.004
1 *year after*				0.002
				0.004
2/3 *years after*				-0.001
				0.002
R^2	0.143	0.143	0.143	0.135
N	20,357	20,357	20,357	9,715

(*continued*)

Table 7: (continued)

	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)
	Inventory dependence		Inventory dependence		Inventory dependence	
	Low	High	Low	High	Low	High
	ITC incr		*ITC incr* $\geq 1\%$		ΔITC (continuous)	
Panel B: One-way-sorted						
B1 Change in fixed investment						
$\Delta ITC_{s,t}$	**0.010*****	**0.000**	**0.012*****	**0.001**	**0.238***	**0.027**
	(*diff. p value* = .04)		(*diff. p value* = .03)		(*diff. p value* = .11)	
R^2	0.101	0.072	0.101	0.072	0.100	0.072
B2 Change in inventory investment						
$\Delta ITC_{s,t}$	0.002	-0.004	0.001	0.001	-0.024	-0.121
	(*diff. p value* = .57)		(*diff. p value* = .97)		(*diff. p value* = .69)	
R^2	0.140	0.162	0.140	0.162	0.140	0.162
N	6,791	6,782	6,791	6,782	6,791	6,782
Panel C: Two-way-sorted (pre-sorted on the SA index)						
C1 Change in fixed investment						
$\Delta ITC_{s,t}$	**0.009****	**-0.003**	**0.012****	**-0.004**	**0.154**	**-0.034**
	(*diff. p value* = .01)		(*diff. p value* = .00)		(*diff. p value* = .18)	
R^2	0.098	0.076	0.098	0.076	0.097	0.076
C2 Change in inventory investment						
$\Delta ITC_{s,t}$	-0.001	-0.007	0.000	-0.004	-0.009	-0.250
	(*diff. p value* = .58)		(*diff. p value* = .75)		(*diff. p value* = .40)	
R^2	0.127	0.163	0.127	0.163	0.127	0.162
N	6,874	6,654	6,874	6,654	6,874	6,654
Panel D: Propensity-score-matched						
D1 Change in fixed investment						
$\Delta ITC_{s,t}$	**0.021****	**0.002**	**0.025*****	**0.002**	**0.482***	**0.008**
	(*diff. p value* = .04)		(*diff. p value* = .03)		(*diff. p value* = .11)	
R^2	0.128	0.087	0.129	0.087	0.126	0.087
D2 Change in inventory investment						
$\Delta ITC_{s,t}$	0.002	-0.011	0.002	-0.007	-0.054	-0.377
	(*diff. p value* = .32)		(*diff. p value* = .50)		(*diff. p value* = .26)	
R^2	0.060	0.204	0.060	0.203	0.060	0.204
N	2,698	2,698	2,698	2,698	2,698	2,698

Table 8: Allocation of internal funds

Reports the estimation results of the system of equations outlined in Equation (20). All dependent variables are scaled by the lagged assets $A_{i,t-1}$. $CFADJ_{i,t}$ is a measure of internal funds adjusted for various non-cash items. The sample consists of the U.S. manufacturing firms from 1980−2015. Each regression includes year and firm fixed effects, $Q_{i,t-1}$, $R^{ex}_{i,t-1}$, $\ln A_{i,t-1}$, and $Leverage_{i,t-1}$. Section 4 describes in detail the data and the sample sorting and matching procedures used to prepare the NDEP subsamples. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively, based on standard errors clustered at the firm level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Dependent variables (scaled by the beginning-of-year assets)								
	I^K	I^N	$NetAcq$	$\Delta ONWC$	$\Delta Cash$	Div	$EquityIss$	$DebtIss$	$\Delta STDebt$
Panel A: Whole sample									
$CFADJ_{i,t}$	**0.107*****	**0.189*****	**0.087*****	**0.186*****	**0.317*****	**0.015*****	**-0.024*****	**-0.015***	**-0.060*****
	0.004	0.005	0.006	0.006	0.009	0.001	0.008	0.008	0.004
R^2 $(within)$	0.144	0.133	0.030	0.033	0.071	0.077	0.059	0.085	0.033
N	27,315	27,315	27,315	27,315	27,315	27,315	27,315	27,315	27,315
Panel B: One-way-sorted subsamples									
Low NDEP	**0.163*****	**0.092*****	**0.116*****	**0.135*****	**0.252*****	**0.017*****	**-0.143*****	**-0.025**	**-0.056*****
	0.008	0.006	0.013	0.011	0.017	0.002	0.016	0.016	0.008
High NDEP	**0.071*****	**0.239*****	**0.072*****	**0.201*****	**0.369*****	**0.013*****	**0.032*****	**-0.016**	**-0.051*****
	0.005	0.010	0.009	0.011	0.014	0.002	0.013	0.013	0.007
Panel C: Two-way-sorted (pre-sorted on the SA index)									
Low NDEP	**0.153*****	**0.104*****	**0.103*****	**0.151*****	**0.267*****	**0.014*****	**-0.120*****	**-0.026***	**-0.061*****
	0.008	0.006	0.012	0.011	0.017	0.002	0.016	0.015	0.007
High NDEP	**0.075*****	**0.245*****	**0.068*****	**0.192*****	**0.342*****	**0.015*****	**0.025****	**-0.034****	**-0.052*****
	0.005	0.010	0.010	0.011	0.014	0.002	0.012	0.014	0.007
Panel D: Two-way-sorted (pre-sorted on credit rating)									
Low NDEP	**0.138*****	**0.079*****	**0.114*****	**0.143*****	**0.258*****	**0.016*****	**-0.175*****	**-0.025**	**-0.052*****
	0.008	0.006	0.014	0.012	0.018	0.003	0.018	0.017	0.008
High NDEP	**0.069*****	**0.226*****	**0.082*****	**0.214*****	**0.356*****	**0.012*****	**0.021**	**-0.021**	**-0.041*****
	0.005	0.010	0.010	0.012	0.016	0.002	0.014	0.014	0.008
Panel E: Propensity-score-matched									
Low NDEP	**0.161*****	**0.092*****	**0.101*****	**0.188*****	**0.317*****	**0.010*****	**-0.050****	**-0.010**	**-0.070*****
	0.011	0.008	0.017	0.016	0.025	0.004	0.024	0.021	0.011
High NDEP	**0.074*****	**0.218*****	**0.082*****	**0.161*****	**0.394*****	**0.017*****	**0.047****	**-0.050****	**-0.051*****
	0.008	0.014	0.016	0.017	0.023	0.003	0.020	0.021	0.011

Table 9: Internal funds and external financing sources

Reports the estimation results of Equations (13) and (14), augmented with $CFADJ_{i,t}$, $EquityIssue_{i,t}$ and $DebtIssue_{i,t}$ in place of $x_{i,t}$ and $x_{i,t-1}$, all scaled by the lagged assets $A_{i,t-1}$. The dependent variable is fixed investment or inventory investment, scaled by $A_{i,t-1}$. The sample consists of the U.S. manufacturing firms from 1980−2015. Each regression includes year and firm fixed effects, $Q_{i,t-1}$, $R^{ex}_{i,t-1}$, $\ln A_{i,t-1}$, and $Leverage_{i,t-1}$. Section 4 describes in detail the data and the sample sorting and matching procedures used to prepare the NDEP subsamples. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively, based on standard errors clustered at the firm level.

	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)
			Dependent two-way-sorted				Propensity-score-matched	
	One-way-sorted		Pre-sorted on SA index		Pre-sorted on rating			
	Inventory dependence		Inventory dependence		Inventory dependence		Inventory dependence	
	Low	High	Low	High	Low	High	Low	High
Panel A: Fixed investment								
$CFADJ_{i,t}$	**0.168*****	**0.068*****	**0.159*****	**0.075*****	**0.139*****	**0.064*****	**0.161*****	**0.076*****
	(*diff. p value* = .00)		(*diff. p value* = .00)		(*diff. p value* = .00)		(*diff. p value* = .00)	
$EquityIssue_{i,t}$	**0.067*****	**0.040*****	**0.066*****	**0.047*****	**0.055*****	**0.036*****	**0.062*****	**0.038*****
	(*diff. p value* = .02)		(*diff. p value* = .06)		(*diff. p value* = .07)		(*diff. p value* = .11)	
$DebtIssue_{i,t}$	**0.125*****	**0.100*****	**0.140*****	**0.083*****	**0.131*****	**0.071*****	**0.159*****	**0.087*****
	(*diff. p value* = .10)		(*diff. p value* = .00)		(*diff. p value* = .00)		(*diff. p value* = .00)	
R^2 (*within*)	0.172	0.139	0.179	0.145	0.165	0.131	0.192	0.139
Panel B: Inventory investment								
$CFADJ_{i,t}$	**0.107*****	**0.251*****	**0.116*****	**0.260*****	**0.096*****	**0.233*****	**0.101*****	**0.256*****
	(*diff. p value* = .00)		(*diff. p value* = .00)		(*diff. p value* = .00)		(*diff. p value* = .00)	
$EquityIssue_{i,t}$	**0.034*****	**0.090*****	**0.038*****	**0.108*****	**0.032*****	**0.076*****	**0.032*****	**0.108*****
	(*diff. p value* = .00)		(*diff. p value* = .00)		(*diff. p value* = .00)		(*diff. p value* = .01)	
$DebtIssue_{i,t}$	**0.084*****	**0.206*****	**0.082*****	**0.199*****	**0.081*****	**0.192*****	**0.092*****	**0.172*****
	(*diff. p value* = .00)		(*diff. p value* = .00)		(*diff. p value* = .00)		(*diff. p value* = .00)	
R^2 (*within*)	0.115	0.175	0.111	0.182	0.106	0.167	0.116	0.168
N	8,885	8,850	8,743	8,719	7,424	7,432	3,850	3,850

Table 10: All industrial firms with the data on input-inventory investment

Reports the estimation results of Equations (13) and (14), where the dependent variables are fixed investment $I_{i,t}^{K}$ and input-inventory investment $I_{i,t}^{N^{inp}}$, scaled by the lagged assets. The sample consists of the non-regulated U.S. firms that have valid data on input inventory from 1980−2015. Regressions in Panels A−C and E include year and firm fixed effects, $Q_{i,t-1}$, $R_{i,t-1}^{ex}$, $\ln A_{i,t-1}$, and $Leverage_{i,t-1}$, whereas regressions in Panel D include firm fixed effects, $Q_{i,t-1}$, $R_{i,t-1}^{ex}$, $\ln A_{i,t-1}$, $Leverage_{i,t-1}$, $CF_{i,t}$, and GDP growth. Section 4 describes in detail the data and the sample sorting and matching procedures used to prepare the NDEP subsamples. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively, based on standard errors clustered at the firm level.

	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)
			Dependent two-way-sorted				Propensity-	
	One-way-sorted		Pre-sorted on SA index		Pre-sorted on rating		score-matched	
	Inventory dependence		Inventory dependence		Inventory dependence		Inventory dependence	
	Low	High	Low	High	Low	High	Low	High
Panel A: Profitability $(x_{i,t} = CF_{i,t})$								
A1 Fixed investment								
sum $[x_{i,t},\ x_{i,t-1}]$	**0.236*****	**0.084*****	**0.222*****	**0.087*****	**0.158*****	**0.076*****	**0.220*****	**0.118*****
	(*diff. p value* = .00)		(*diff. p value* = .00)		(*diff. p value* = .00)		(*diff. p value* = .00)	
A2 Inventory investment								
sum $[x_{i,t},\ x_{i,t-1}]$	**0.044*****	**0.136*****	**0.041*****	**0.141*****	**0.029*****	**0.131*****	**0.046*****	**0.152*****
	(*diff. p value* = .00)		(*diff. p value* = .00)		(*diff. p value* = .00)		(*diff. p value* = .00)	
N	7,743	7,531	7,484	7,646	6,596	6,507	2,643	2,643
Panel B: Industry-peer net asset growth $\left(x_{i,t} = IndNAGR_{i,j,t}^{-i}\right)$								
B1 Fixed investment								
sum $[x_{i,t},\ x_{i,t-1}]$	**0.128*****	**0.085*****	**0.116*****	**0.069*****	**0.087*****	**0.045*****	**0.165*****	**0.086*****
	(*diff. p value* = .07)		(*diff. p value* = .05)		(*diff. p value* = .07)		(*diff. p value* = .07)	
B2 Inventory investment								
sum $[x_{i,t},\ x_{i,t-1}]$	**0.030*****	**0.128*****	**0.033*****	**0.118*****	**0.022*****	**0.100*****	**0.045*****	**0.120*****
	(*diff. p value* = .00)		(*diff. p value* = .00)		(*diff. p value* = .00)		(*diff. p value* = .00)	
N	7,691	7,494	7,451	7,595	6,562	6,486	2,643	2,643
Panel C: Industry-peer sales growth $\left(x_{i,t} = IndSGR_{i,j,t}^{-i}\right)$								
C1 Fixed investment								
sum $[x_{i,t},\ x_{i,t-1}]$	**0.107*****	**0.068*****	**0.100*****	**0.052*****	**0.074*****	**0.035*****	**0.151*****	**0.074*****
	(*diff. p value* = .05)		(*diff. p value* = .02)		(*diff. p value* = .05)		(*diff. p value* = .06)	
C2 Inventory investment								
sum $[x_{i,t},\ x_{i,t-1}]$	**0.016*****	**0.064*****	**0.014****	**0.070*****	**0.017*****	**0.042****	**0.020****	**0.081*****
	(*diff. p value* = .01)		(*diff. p value* = .00)		(*diff. p value* = .09)		(*diff. p value* = .04)	
N	7,691	7,494	7,451	7,595	6,562	6,486	2,643	2,643

(*continued*)

Table 10: (continued)

	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)
			Dependent two-way-sorted				Propensity-score-matched	
	One-way-sorted		Pre-sorted on SA index		Pre-sorted on rating			
	Inventory dependence		Inventory dependence		Inventory dependence		Inventory dependence	
	Low	High	Low	High	Low	High	Low	High
Panel D: Economic policy uncertainty								
D1 Fixed investment								
$-\ln PU_t^{BBD}$	**0.013*****	**0.005*****	**0.011*****	**0.005****	**0.010*****	**0.005****	**0.015*****	**0.003**
	(*diff. p value* = .00)		(*diff. p value* = .04)		(*diff. p value* = .06)		(*diff. p value* = .01)	
D2 Inventory investment								
$-\ln PU_t^{BBD}$	**0.002*****	**0.014*****	**0.003*****	**0.012*****	**0.002***	**0.013*****	**0.003****	**0.014*****
	(*diff. p value* = .00)		(*diff. p value* = .00)		(*diff. p value* = .00)		(*diff. p value* = .00)	
N	7,128	7,118	7,156	7,015	7,116	7,130	2,450	2,450
Panel E: Internal and external funds								
E1 Fixed investment								
$CFADJ_{i,t}$	**0.187*****	**0.074*****	**0.171*****	**0.076*****	**0.130*****	**0.065*****	**0.201*****	**0.093*****
	(*diff. p value* = .00)		(*diff. p value* = .00)		(*diff. p value* = .00)		(*diff. p value* = .00)	
$EquityIssue_{i,t}$	**0.079*****	**0.038*****	**0.070*****	**0.036*****	**0.060*****	**0.032*****	**0.084*****	**0.024**
	(*diff. p value* = .01)		(*diff. p value* = .02)		(*diff. p value* = .04)		(*diff. p value* = .03)	
$DebtIssue_{i,t}$	**0.123*****	**0.106*****	**0.138*****	**0.094*****	**0.126*****	**0.084*****	**0.110*****	**0.070*****
	(*diff. p value* = .33)		(*diff. p value* = .02)		(*diff. p value* = .04)		(*diff. p value* = .12)	
E2 Inventory investment								
$CFADJ_{i,t}$	**0.052*****	**0.153*****	**0.055*****	**0.152*****	**0.038*****	**0.143*****	**0.052*****	**0.159*****
	(*diff. p value* = .00)		(*diff. p value* = .00)		(*diff. p value* = .00)		(*diff. p value* = .00)	
$EquityIssue_{i,t}$	**0.022*****	**0.046*****	**0.016*****	**0.060*****	**0.015*****	**0.049*****	**0.022*****	**0.029*****
	(*diff. p value* = .02)		(*diff. p value* = .00)		(*diff. p value* = .00)		(*diff. p value* = .38)	
$DebtIssue_{i,t}$	**0.046*****	**0.101*****	**0.045*****	**0.100*****	**0.044*****	**0.089*****	**0.053*****	**0.082*****
	(*diff. p value* = .00)		(*diff. p value* = .00)		(*diff. p value* = .00)		(*diff. p value* = .08)	
N	6,355	6,390	6,413	6,261	5,501	5,510	2,041	2,041

Table 11: GMM results

Reports the GMM estimation results of Equations (13) and (14), where the dependent variables are fixed investment and inventory investment, scaled by the lagged assets. The sample consists of the U.S. manufacturing firms from 1980−2015. Section 4 describes in detail the data and the sample sorting and matching procedures used to prepare the NDEP subsamples. The second and third lags of Q are used as instruments for AB-GMM (Panel A), and the fifth-order cumulant estimator is used for EJW-GMM (Panel B). See Section 6 for the GMM estimation procedures in detail. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively, based on standard errors clustered at the firm level.

	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)
			Dependent two-way-sorted				Propensity-	
	One-way-sorted		Pre-sorted on SA index		Pre-sorted on rating		score-matched	
	Inventory dependence		Inventory dependence		Inventory dependence		Inventory dependence	
	Low	High	Low	High	Low	High	Low	High
Panel A: AB-GMM								
A1 Fixed investment								
$CF_{i,t}$	**0.105*****	**0.043*****	**0.096*****	**0.030****	**0.081*****	**0.048*****	**0.132*****	**0.024**
	(*diff. p value* = .01)		(*diff. p value* = .01)		(*diff. p value* = .05)		(*diff. p value* = .01)	
J-stat p-value	0.591	0.523	0.888	0.580	0.665	0.920	0.791	0.320
A2 Inventory investment								
$CF_{i,t}$	**0.116*****	**0.252*****	**0.115*****	**0.260*****	**0.080*****	**0.227*****	**0.131*****	**0.285*****
	(*diff. p value* = .00)		(*diff. p value* = .00)		(*diff. p value* = .00)		(*diff. p value* = .01)	
J-stat p-value	0.151	0.940	0.212	0.362	0.263	0.602	0.278	0.777
N	11,300	10,938	11,059	11,158	9,456	9,158	4,613	4,613
Panel B: EJW-GMM								
B1 Fixed investment								
$CF_{i,t}$	**0.140*****	**0.035****	**0.132*****	**0.039****	**0.127*****	**0.017**	**0.142*****	**0.072*****
	(*diff. p value* = .00)		(*diff. p value* = .00)		(*diff. p value* = .00)		(*diff. p value* = .00)	
ρ^2 (EW)	0.088	0.080	0.081	0.097	0.080	0.100	0.094	0.078
B2 Inventory investment								
$CF_{i,t}$	**0.090*****	**0.333*****	**0.081*****	**0.358*****	**0.065*****	**0.328*****	**0.073*****	**0.464*****
	(*diff. p value* = .00)		(*diff. p value* = .00)		(*diff. p value* = .00)		(*diff. p value* = .01)	
ρ^2 (EW)	0.037	0.063	0.043	0.074	0.036	0.065	0.046	0.043
N	12,336	12,313	12,425	12,215	10,292	10,247	5,088	5,088

Table A 1: Model parameter values

Reports the parameter values used to solve the investment model. See Appendix A for the calibration in detail.

Parameter	Notation	Value
Persistence of productivity	ρ_x	$0.7^{1/4}$
Conditional volatility of productivity	σ_x	$0.29\frac{1}{\sqrt{4}}$
Depreciation rate of fixed capital	δ_k	$0.12\frac{1}{4}$
Depreciation rate of inventory	δ_n	$0.24\frac{1}{4}$
Return-to-scale	α	0.7
Fixed operating cost	f	$0.4\frac{1}{4}$
Adjustment cost coefficient for fixed capital	c_k	8
Adjustment cost coefficient for inventory	c_n	2
Complementarity (parameter for the ES)	γ	$\{0.1, 1, 3\}$
Discount rate	r	$0.05\frac{1}{4}$