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journal homepage: [www.elsevier.com/locate/jfec](http://www.elsevier.com/locate/jfec)Inventory investment and the cost of capital<sup>☆</sup>Christopher S. Jones<sup>1</sup>, Selale Tuzel\*

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## ABSTRACT

We examine the relation between inventory investment and the cost of capital in the time series and the cross section. We find consistent evidence that risk premiums, rather than real interest rates, are strongly negatively related to future inventory growth at the aggregate, industry, and firm levels. The effect is stronger for firms in industries that produce durables rather than nondurables, exhibit greater cyclicality in sales, require longer lead times, and are subject to more technological innovation. We then construct a production-based asset pricing model with two types of capital, fixed capital and inventories, to explain these empirical findings. Convex adjustment costs and a countercyclical price of risk lead to negative time series and cross-sectional relations between expected returns and inventory growth.

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## 1. Introduction

As a form of investment, a firm's optimal inventory stock should naturally be expected to vary with its cost of capital. At a macro level, we would expect aggregate inventory investment to vary with measures of the average cost of capital. One of the puzzling results from the empirical macroeconomic literature on inventories is the apparent lack of relation between the accumulation of

inventories and the cost of capital, at least as proxied by short-term real interest rates. Maccini, Moore, and Schaller (2004) note that although there is a “perception of an inverse relationship between inventory investment and interest rates, ... almost no evidence exists for such an effect.” Given that inventory investment contributes more to fluctuations in the gross domestic product (GDP) than either consumption or fixed investment, the inability to relate inventory investment to the cost of capital is disconcerting. A limitation of prior work is that it generally focuses on the real interest rate as the cost of capital relevant for determining inventory investment decisions. If inventory investment is risky, however, then the real interest rate may be a poor proxy for the relevant cost of capital.

The primary goal of our paper is to investigate the relationship between risk premiums and inventory investment. We find strong empirical evidence that risk premiums predict inventory growth at the aggregate, industry, and firm levels. Specifically, a higher risk premium predicts lower aggregate inventory growth, particularly in industries where inventory investment is likely

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to be riskier. At the firm level, both time series and cross-sectional variation in the cost of equity capital drive inventory investment. We then ask whether a production-based asset pricing model with aggregate and idiosyncratic productivity shocks can explain these findings. In the model, which generates both the time series and cross section of firm investment behavior, we find a negative relationship between the cost of capital and inventory investment that is generally consistent with our empirical results.

We find that aggregate inventory investment is negatively related to both debt and equity cost of capital measures constructed from standard regressions of excess returns on predictive variables. We then investigate whether the forms of inventory investment with a greater exposure to systematic risk are more sensitive to these measures. While many types of inventories, like food or tobacco, would appear to carry little systematic risk, other types may be risky for a number of reasons. The value of commodity-like inventories, for instance, might fluctuate substantially with macroeconomic growth. Other goods, like automobiles, which are held in finished goods inventory for longer amounts of time, may face considerable demand risk over the period from when they are produced until when they are sold. This demand risk may be even more substantial for work in progress inventories of goods that require a substantial amount of time to produce.

We find that the relation between the risk premium and inventory investment is stronger for durable goods than it is for nondurables. As noted by Yogo (2006), expenditures are more strongly procyclical for durable goods than they are for nondurables. In our sample, the beta of a regression of durable expenditure growth on GDP growth is around 2.5 times as large as the corresponding beta for nondurables. This greater sensitivity to the business cycle should naturally make investment in durable inventories more risky and therefore more sensitive to aggregate risk premiums.

Our empirical work also separates input inventories (raw materials and work in progress) from output inventories (finished goods). It is well known that these two types are qualitatively different. Input inventories are larger and, at least in the case of durable goods, exhibit greater volatility and are more procyclical. Though we find some sensitivity to risk premiums in both input and output inventories, the effect is weaker for output inventories. This may be the result of output inventories, being finished goods that are ready to be sold, being less risky than input inventories, which take time to transform into final products. This would be consistent with the relative lack of cyclical behavior we observe in output inventories.

Our regressions also control for variation in the ex ante real interest rate. As in prior research, we find no relation between the real rate and inventory investment. A potential explanation is that, in contrast to risk premiums, volatility in real rates was quite low over much of the post-war sample period. With a data set covering 1953–1971, for instance, Fama (1975) fails to reject the hypothesis of constant ex ante real rates. While subsequent rates have proved significantly more volatile, it is likely that

they still represent the least volatile component of the average firm's cost of capital. If inventories are sufficiently risky, then the variation in the real interest rate might be only weakly related to the appropriate cost of capital.

We further disaggregate the data by examining inventory growth patterns in 12 different manufacturing industries. Although we find that the relation between inventory growth and risk premiums is only significant for six or seven of them, the effect is stronger for those industries, like transportation equipment, whose sales covary most positively with aggregate GDP growth, than for other industries, like food, whose sales are relatively flat across the business cycle. The effect is also stronger in high-patent industries, where changing technologies may cause inventories to become obsolete more quickly. Finally, the effect is stronger in industries with longer lead times, which make inventories a longer-term and hence riskier commitment.

At the firm level, we examine the relation between the cost of capital and inventory investment using several different approaches. First, we find that the implied cost of equity capital constructed from projected firm earnings and current market prices is strongly related to future inventory growth. We obtain this result both in Fama-MacBeth regressions and in panel regressions with firm fixed effects, indicating that the cost of capital's effect on inventories has both time series and cross-sectional components. We find similar results whether we use a cost of capital constructed from analyst earnings forecasts (Gebhardt, Lee, and Swaminathan, 2001) or measures based on forecasts from statistical models (Hou, van Dijk, and Zhang, 2012; Wu and Zhang, 2011).

We also confirm earlier findings (e.g., Thomas and Zhang, 2002; Belo and Lin, 2012) that portfolios formed on the basis of inventory growth exhibit a substantial spread in future excess returns, with the returns of low inventory growth firms exceeding those of high growth firms by 5.73% per year. This, too, is consistent with a negative relationship between inventory growth and the cost of capital (e.g., Wu, Zhang, and Zhang, 2010). In a refinement to this result, we then decompose this return spread into industry and firm components. We find that roughly half of the spread between high and low inventory growth portfolios is firm-specific and half is industry-related. Furthermore, firms in the extreme quintile portfolios tend to come from industries that are significantly riskier than average. These results provide additional evidence that inventory growth at the industry level is related to the cost of capital, and that industry heterogeneity is an important feature of the data.

We then build a theoretical model to investigate the relation between inventory investment and risk premiums at the firm and aggregate levels. Our model economy is populated by many firms producing a homogeneous good using two types of capital, namely fixed capital and inventories, and labor. Our production function follows Kydland and Prescott (1982) and Christiano (1988), where production requires investment in both fixed capital and inventories. Like Kydland and Prescott, we introduce a friction into the adjustment of the capital stock, but we replace Kydland and Prescott's time-to-build constraint

with a simple adjustment cost that has the effect of smoothing the capital used in production. Firms take the stochastic discount factor and the wage rate as given, and both are specified exogenously. The pricing kernel, similar to those of Berk, Green, and Naik (1999) and Zhang (2005), generates realistic asset pricing implications, such as the level, volatility, and predictability of excess stock market returns. Our stochastic wage rate follows Bazzdrusch, Belo, and Lin (2009) in postulating a positive relation between aggregate productivity and wages.

As in the earlier seminal work, we model inventories as a factor of production, a framework that has been adopted more recently by Belo and Lin (2012), Gomes, Kogan, and Yogo (2009), and (in a model with working capital rather than inventories) by Wu, Zhang, and Zhang (2010). Using inventories as a factor of production can be motivated in several ways. By investing more in inventories, firms can reduce the number of costly factory changeovers in which the capital stock is reconfigured to produce a different output good. Alternatively, if the firm faces fluctuating demand or supply, then holding inventories can ensure high capacity utilization, and thus high production output for a given level of capital.

In simulations of our model, calibrated to match aggregate stock return dynamics, we replicate the negative relationship between inventory investment and the cost of capital. In both aggregate and firm-level regressions using simulated model data, coefficients on the cost of capital are in line with those from our empirical analysis. We then assess the ability of the model to explain the return spread between high and low inventory growth portfolios. Our benchmark calibration generates a 3.5% spread, which is about two-thirds of the full spread observed in the data. However, given that industries are absent from our model, and because our model is parameterized based on estimates of firm-level productivity shocks that exclude industry effects, the industry-adjusted return spread is a more appropriate target. On this basis the model performs well.

We also find that a higher degree of complementarity between fixed capital and inventories strengthens the relationship between inventory investment and the cost of capital. Specifically, the calibrations that feature greater complementarity generate a larger spread between low and high inventory growth portfolio returns. Higher complementarity reduces the firm's flexibility in responding to shocks because it reduces their ability to substitute inventories, which have low adjustment costs, for fixed capital.

While we are unaware of other work that examines the relationship between risk premiums and inventory investment at the aggregate level, there is a substantial related literature that examines cross-sectional relationships between firm returns, inventory investment, and accruals. Sloan (1996) documents that firms with high levels of accruals, of which the change in inventories is one component, significantly underperform those with low accruals. Thomas and Zhang (2002) refine this result by demonstrating that the component of accruals that seems to drive the anomaly discovered by Sloan is in fact the change in inventories. Wu, Zhang, and Zhang (2010) propose that the accruals phenomenon is in fact consistent with the

optimal investment behavior of firms in a  $q$ -theoretical framework; hence, is not necessarily an anomaly. They model accruals as an input to the production of the firm (i.e., an investment good) and find, within the model, that they respond to changes in discount rates. They argue that this channel can explain the negative relationship between accruals and future returns in the cross section and present several empirical findings in support of this hypothesis. Finally, Belo and Lin (2012) find that, after controlling for firm size, firms with higher inventory growth earn lower returns. Similar to our paper, they perform a quantitative assessment of this observation within a partial equilibrium model with convex and nonconvex adjustment costs. As in our results, they find that the cross-sectional spread in firm returns is somewhat large relative to the spread generated by their calibrated model, though they argue that accounting for leverage closes the gap between spreads in the model and in the data.

The next section of the paper contains empirical results on the relationship between inventories and the cost of capital at the aggregate, industry, and firm levels. Section 3 proposes and solves a simple equilibrium model in which firms invest in both capital goods and inventories. We conclude in Section 4.

## 2. Empirical analysis

Our interest is in the empirical relation between inventory investment and the cost of capital, controlling for other factors that past theory or empirical work has found to be relevant. We examine time series or pooled time series/cross-sectional regressions of the form:

$$\Delta \ln N_t = b_0 + b_1 \ln(N_{t-1}/Y_{t-1}) + b_2 E_{t-1}[\Delta \ln Y_t] + b_3 E_{t-1}[RF_t] + b_4 E_{t-1}[RP_t] + \epsilon_t, \quad (1)$$

where  $N_t$  denotes inventories at the end of month  $t$ ,  $Y_t$  denotes month- $t$  sales,  $RF_t$  is the ex post real rate of return on a short-term nominal bond, and where  $RP_t$  denotes some measure of the risk premium, either the excess return on a portfolio of stocks or bonds.

Each term in the regression has a simple interpretation. The ratio of past inventories to sales,  $N_{t-1}/Y_{t-1}$ , arises as in Lovell (1961) from a target adjustment motive, and we would expect a negative coefficient on this term. The effect of higher expected sales growth,  $E_{t-1}[\Delta \ln Y_t]$ , is somewhat indeterminate. If inventories are primarily used to smooth production, then we might expect  $b_2$  to be negative. If, on the other hand, inventories serve mainly to avoid stock-outs, then  $b_3$  should be positive. Finally, the two components of the cost of capital,  $E_{t-1}[RF_t]$  and  $E_{t-1}[RP_t]$ , are included given the focus of our paper.

A complication in estimating the model above is the unobservability of the expectations on the right-hand side of the regression. In aggregate and industry regressions, we address this issue by using a two-stage least squares approach in which estimates of a risk premium and an expected sales growth rate from standard predictive regressions are used as explanatory variables in (1). In firm-level regressions, we proxy for risk premiums using implied costs of capital.

## 2.1. Data

Our primary data source for aggregate- and industry-level regressions is the Manufacturers' Shipments, Inventories, and Orders (M3) database from the U.S. Census. From this database we obtain monthly values for aggregate and disaggregate sales (shipments) and inventories. We convert to quarterly by summing sales within each quarter and taking the end-of-quarter values of inventories. The data are available in seasonally adjusted form, but they are nominal. We compute real series using the appropriate Producer Price Index (PPI) from the Bureau of Labor Statistics.

We use inventory and shipment data for all manufacturing goods and for 12 different industries within the manufacturing sector. Each industry is classified in the database as either a durable or nondurable producer, and we also consider aggregations of the durable and nondurable sectors. The database also contains unfilled orders for most durable goods industries and, through March 2001, for aggregate nondurable goods. It also separates inventories into raw materials, work in progress, and finished goods. Following Humphreys, Maccini, and Schuh (2001), we refer to the sum of raw materials and work in progress as "input" inventories and to finished goods as "output inventories." Additional details on our use of M3 data can be found in the Appendix. GDP growth rates, used to measure industry cyclicity, are computed from the quarterly per capita real GDP series from the Bureau of Economic Analysis National Income and Product Accounts (NIPA) tables. The corresponding GDP deflator is used to transform firm-level variables to real values.

We augment these quantity variables with financial asset returns and predictive variables from several sources. Nominal riskless returns and Fama and French (1993) factor returns are from Ken French's Web site. The returns on long-term corporate and Treasury bonds are from Ibbotson and Associates. Real risk-free returns are computed by subtracting Consumer Price Index growth from French's riskless nominal returns.

We compute the term spread as the difference between the 10-year and 3-month Treasury yields. These data are from the Federal Reserve's H15 database. Prior to 1962 we use monthly averages, but starting in 1962 we use month-end values. The default spread is computed as the difference between Moody's average BAA bond yield and the 10-year Treasury yield. These are also obtained from H15 data, but both yields are monthly averages.

We compute the dividend yield as the 1-year moving average of past Standard & Poor's (S&P) Composite dividends divided by the current level of the S&P Composite Index, where both data series are from Robert Shiller's Web site. Data on CAY, the consumption-wealth ratio of Lettau and Ludvigson (2001), is from Martin Lettau's Web site. Our final predictor is the log ratio of new orders to shipments of durable goods from Jones and Tuzel (in press).<sup>1</sup>

<sup>1</sup> The construction of  $\ln NO/S$ , the log ratio of new orders to shipments, is slightly different here than in Jones and Tuzel (in press).

Sales (sale) and inventory (invt) data for firm-level regressions come from Compustat. Several control variables are also constructed from Compustat data. Kashyap, Lamont, and Stein's (1994) liquidity variable is equal to cash and short-term investments (che) divided by total assets (at). Carpenter, Fazzari, and Petersen (1994, 1998) propose two other variables that we use as controls, namely the ratio of cash flow to assets and a measure of interest rate coverage. Cash flow is equal to earnings before extraordinary items (ibc) plus depreciation (dpc), while our coverage variable (which is inversely related to coverage) is equal to interest expenses (xint) divided by the sum of interest expenses and cash flow. A final control variable, firm size, is defined as the December market capitalization from CRSP.

We employ three cost of capital measures in the firm-level regressions. Each measure is the solution to a present value equation in which projected firm earnings are used to compute equity values under the discounted residual income model. Our primary measure, in which earnings projections are set equal to consensus analyst forecasts, uses the method of Gebhardt, Lee, and Swaminathan (2001). A second measure, from Hou, van Dijk, and Zhang (2012), is based on regression forecasts of the level of firm earnings. A third, from Wu and Zhang (2011), uses a regression to forecast firm ROE instead, which may avoid problems associated with the nonstationarity of earnings levels.

We impose modest filters on the firm-level sample to focus attention on firms for which inventories are relevant. We exclude regulated firms (SIC codes between 4900 and 4999) as well as financial firms (SIC codes between 6000 and 6999), and we require that firms have nonmissing data for inventories, sales, book equity, and total assets. We exclude firms that have fiscal year-ends between January and May, and we discard the first two years of data for each firm to eliminate survivor bias, as in Belo and Lin (2012). We are able to match regression estimates from Hou, van Dijk, and Zhang (2012) and Wu and Zhang (2011) most closely when we follow Fama and French (2006) and require firms to have book equity above \$12.5 million and total assets above \$25 million. Regressions that use the cost of capital estimates from these papers therefore impose that filter.<sup>2</sup>

Finally, we use the ratio of patents to shipments as a measure of how fast an industry's products become obsolete. The patent data are from the U.S. Patent and Trademark Office and are available annually over the period from 1963 to 2008 for all industries except

(footnote continued)

In that paper, we noted that the new orders series produced by the U.S. Census did not include any orders from the semiconductor series, even though semiconductors were included in shipments. For comparability, we therefore removed semiconductors from the shipments series. Unfortunately, in mid-2010, the Census stopped providing the semiconductor shipments data. We now subtract all electronics from both new orders and shipments, which again makes the two series comparable. The new  $\ln NO/S$  series has a correlation of 0.993 with the original.

<sup>2</sup> When we eliminate the filter, the significance of our results increases, in some cases substantially. We impose the filter for comparability with existing work.

**Table 1**

Predictive regressions.

In this table we regress current values of sales growth, real risk-free returns, and two excess return measures on lagged predictive variables. Values reported are OLS regression coefficients and  $t$ -statistics, where standard errors are computed using the Newey and West (1987) procedure with four lags. Where noted, coefficient estimates have been multiplied by 100. The excess return measures are the return on long-term corporate bonds minus the one-month Treasury bill return ( $RBRF_t$ ) and the return on US stock market minus the Treasury bill return ( $RMRF_t$ ). All explanatory variables are lagged and include sales growth ( $\Delta \ln Y_{t-1}$ ), the log ratio of total manufacturing inventories to sales ( $\ln(N_{t-1}/Y_{t-1})$ ), the dividend yield ( $DP_{t-1}$ ), Lettau and Ludvigson's (2001) CAY variable, the term ( $TERM_{t-1}$ ) and default ( $DEF_{t-1}$ ) spreads, the real riskless rate ( $RF_{t-1}$ ) and its four-quarter moving average ( $RF4_{t-1}$ ), and Jones and Tuzel's (in press) log ratio of new orders to sales ( $NO/S_{t-1}$ ). Quantity data are real and seasonally adjusted. Data are quarterly from 1958Q1 to 2010Q4.

Intercept ( $\times 100$ )	$\ln(N_{t-1}/Y_{t-1})$ ( $\times 100$ )	$\Delta \ln Y_{t-1}$	$DP_{t-1}$	$CAY_{t-1}$	$TERM_{t-1}$	$DEF_{t-1}$	$RF_{t-1}$	$RF4_{t-1}$	$NO/S_{t-1}$	Adj. $R^2$ (%)
Sales growth ( $\Delta Y_t$ )										
7.36 (5.72)	6.96 (4.86)	0.18 (1.98)	-0.80 (-4.42)	-0.13 (-1.58)	6.45 (4.82)	-4.85 (-1.48)			0.07 (1.02)	27.74
Real risk-free returns ( $RF_t$ )										
0.08 (1.74)				0.06 (2.05)				0.69 (6.35)		32.53
Excess corporate bond returns ( $RBRF_t$ )										
-0.90 (-1.64)					11.55 (3.55)		-2.03 (-2.25)	2.54 (2.12)	-0.18 (-2.06)	12.72
Excess stock market returns ( $RMRF_t$ )										
-0.70 (-0.33)			0.78 (1.26)	0.62 (1.66)					-0.47 (-2.77)	6.17

petroleum products, for which we obtain data from 1980 to 1998. In addition, the data do not allow us to distinguish between food/kinred products and tobacco patents, so we assume that the patent/sales ratios are identical for both industries. Since the total number of patents in these industries is very low, this assumption is benign.

## 2.2. Predictive regressions

Our empirical approach requires proxies for the expectations that appear as explanatory variables in (1). In this section we outline our approach for variable selection and report the results of forecast regressions for sales growth, real riskless returns, and excess returns on portfolios of risky assets. The sales growth measure we consider is computed from the sales of all manufacturing goods. Below, we will also look at disaggregated data on sales and inventories. When we do, we will use a regression model that is identical to the one we use for all goods except that it will be based on those disaggregated series.

Our approach is to select those predictors that minimize the Akaike Information Criterion (AIC). We search over all possible combinations of predictive variables from a set that includes three lags of sales growth and the logarithm of the lagged inventory/sales ratio, which we compute using both total inventories and input inventories only. We also include seven predictive variables found in prior work to predict excess bond and stock returns. The first is the lagged real return on a nominally riskless asset, and the second is a four-quarter moving average of this variable that is included to capture trends in real rates. The others are the term spread, the default spread, the dividend/price ratio, Lettau and Ludvigson's (2001) CAY variable, and Jones and Tuzel's (in press)

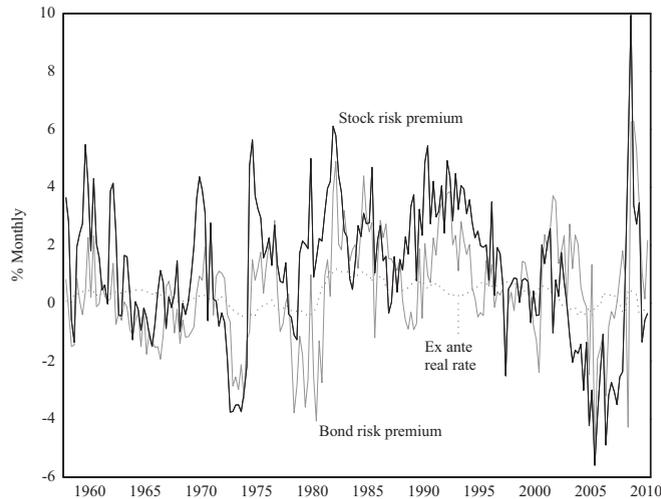
series on the ratio of new orders to shipments of durable goods (NO/S).

Table 1 reports the results of this process. Sales growth is positively related to its first lag and the lagged ratio of total inventories to sales. Several financial variables that are known to forecast asset returns also predict sales growth, a result that is clearly related to earlier findings showing that these variables forecast GDP growth (e.g., Harvey, 1988, Ang, Piazzesi, and Wei, 2006). Finally, the ratio of new orders to shipments of durable goods has some predictive power, echoing the results of Jones and Tuzel (in press).

The remainder of the table contains results on the predictability of various components of the ex post cost of capital. In order to produce cost of capital measures that are consistent with previous literature, we focus on predictors popular in prior literature and specifically exclude lagged sales growth and inventory/sales ratios when finding the minimum AIC predictor sets.

For regressions of real returns on nominal one-month bonds, the specification that minimizes the AIC includes its lagged four-quarter moving average as well as Lettau and Ludvigson's (2001) CAY variable. The predictive regression for  $RBRF$ , the excess returns on Treasury bonds, includes the term spread, the ratio of new orders to shipments, and both the first lag of  $RF$  and its lagged four-quarter moving average. The term spread is the most significant of the four predictors. Finally, the excess stock market return,  $RMRF$ , is forecasted using the dividend yield, CAY, and the ratio of new orders to shipments, with the latter being the most significant.

Fig. 1 plots the fitted values from the three return regressions. It is clearly seen that the amount of variation in bond and stock risk premiums far exceeds that in the ex ante real interest rate. Thus, prior work that focused on the real rate as the sole driver of the cost of capital



**Fig. 1.** Ex ante risk premiums and real rates. This figure shows fitted values from the three return forecasting regressions from Table 1. The solid line represents forecasts of excess stock market returns. The dashed line shows forecasted excess returns on investment grade corporate bonds. The dotted line represents the ex ante real riskless rate. All series are computed using data from 1958Q1 to 2010Q4.

has missed out on the most important drivers of time variation in firm discount rates.

### 2.3. Aggregate inventory regressions

As discussed above, our aggregate-level results will be focused on regressions, like (1), in which one or more explanatory variables are unobserved. We replace these expectations with the fitted values of the predictive regressions estimated in the previous section. Pagan (1984) proves that this procedure is asymptotically efficient, but that an adjustment to ordinary least squares standard errors is required. We use Pagan's approach for computing standard errors, which is based on instrumental variables regression, except that we incorporate the Newey and West (1987) adjustment for heteroskedasticity and autocorrelation.

Table 2 contains results on the relationship between the cost of capital and inventory growth at the aggregate level. Our measures of the cost of capital include the ex ante real interest rate and either the expected excess bond return or the expected excess stock return. Following standard practice, the regressions also include the expected rate of future sales growth and the lagged log ratio of inventories to sales.

The main result of Table 2, observed in the first two regressions, is that risk premiums are strongly and negatively related to future growth in aggregate manufacturing inventories. This holds whether we measure risk premiums using expected excess stock or bond returns.

To better understand the magnitude of the effect, we can multiply the coefficient on a risk premium measure by the standard deviation of the fitted values from the corresponding first-stage regression. For *RBRF*, the coefficient is  $-0.28$ , and the standard deviation of  $E[RBRF]$  is around 0.019, implying that a one standard deviation increase in the bond risk premium reduces quarterly inventory growth by 0.52 percentage points. For *RMRF*,

the corresponding reduction is 0.49 percentage points. Given that the quarterly volatility of inventory growth is 1.6%, this is a substantial effect.

The table also considers durable versus nondurable industries separately in addition to the input and output inventories aggregated across all industries. We do so because of almost certain differences in the riskiness of different types of inventory investment. Durable goods, in particular, have been identified by Yogo (2006) and others as having sales that are particularly sensitive to the business cycle. In addition, they are also significantly longer-lived, which means that any reasonably persistent change in the cost of capital will have much larger effects on the Tobin's  $q$  of durable inventory investment via a "duration" effect.

Consistent with this view, durable inventories indeed display greater sensitivity to fluctuations in the cost of capital, with coefficients that are larger and even more highly significant. In contrast, there is no detectable relation between any cost of capital variable and the growth of nondurable inventories. The latter finding is consistent with nondurable inventories carrying little systematic risk, which is suggested by the less cyclical nature of nondurable sales. It is also possibly related to the fact that delivery lead times (as approximated by the ratio of unfilled orders to shipments) are much higher for durables than they are for nondurables. Over the 1968–2001 period, the longest sample for which nondurable unfilled orders are available, the average ratio of unfilled orders to monthly shipments is just 0.74 for nondurables, indicating a lead time of around three weeks. For durables, over the same period, that figure is around four months. With longer lead times, durable goods producers are more exposed to changes in business conditions because they are less able to slow inventory growth by cutting production. Combined, these factors suggest that investment in durable goods may be significantly riskier and, therefore, more sensitive to the cost of capital.

**Table 2**

Aggregate inventory growth.

In this table we report the results of regressions of aggregate inventory growth rates on an inventory stock measure, expected sales growth, the real riskless interest rate, and a risk premium measure. Values in parentheses are *t*-statistics, computed according to Pagan (1984) except that they include a heteroskedasticity and autocorrelation adjustment with four lags. Where noted, coefficient estimates have been multiplied by one hundred. The inventory growth rate is computed using the specified type of inventory. The same inventory type is also used in the construction of the inventory stock measure,  $\ln(N_{t-1}/Y_{t-1})$ . The sales measure used both in the inventory stock measure and expected sales growth ( $E[\Delta \ln Y_t]$ ) corresponds to the set of industries being analyzed (either all manufacturing, durable, or nondurable). Expected sales growth, the ex ante real rate ( $E[RF_t]$ ), and a risk premium measure (either  $E[RMRF_t]$  or  $E[RBRF_t]$ ) are each computed using the predictive regression results reported in Table 1. Data are quarterly from 1958Q1 to 2010Q4.

Intercept ( $\times 100$ )	$\ln(N_{t-1}/Y_{t-1})$ ( $\times 100$ )	$E[\Delta \ln Y_t]$	$E[RF_t]$	$E[RBRF_t]$	$E[RMRF_t]$	Adj. $R^2$ (%)
All manufacturing						
0.25 (0.34)	0.01 (0.01)	0.33 (2.24)	0.18 (0.40)	-0.28 (-4.65)		10.78
1.93 (2.73)	2.17 (2.10)	0.06 (0.39)	0.16 (0.40)		-0.21 (-4.25)	6.86
Durables only						
0.00 (-0.01)	-0.79 (-0.81)	0.32 (3.08)	0.11 (0.23)	-0.38 (-5.32)		21.69
1.23 (2.41)	1.21 (1.20)	0.09 (0.73)	0.11 (0.25)		-0.29 (-4.58)	14.00
Nondurables only						
1.81 (1.55)	1.73 (1.49)	0.00 (0.00)	0.26 (0.55)	-0.06 (-1.08)		0.05
3.04 (2.68)	2.92 (2.49)	-0.18 (-0.90)	0.33 (0.74)		-0.09 (-1.58)	0.60
Output inventories						
-1.32 (-0.43)	-0.92 (-0.54)	0.12 (0.62)	0.47 (0.86)	-0.20 (-3.31)		1.84
-0.59 (-0.19)	-0.53 (-0.31)	0.04 (0.22)	0.22 (0.44)		-0.03 (-0.44)	-1.60
Input inventories						
0.19 (0.19)	-0.01 (-0.01)	0.45 (3.18)	0.10 (0.23)	-0.32 (-4.89)		16.16
2.90 (2.90)	2.21 (2.40)	0.11 (0.81)	0.15 (0.37)		-0.27 (-5.16)	13.75

Table 2 also shows that there is somewhat more evidence that risk premiums affect investment in input inventories than output inventories. Input inventories, which consist of raw materials and work in progress, may respond more to the cost of capital for several reasons. First, Humphreys, Maccini, and Schuh (2001) note that there is a “relatively weak synchronization of materials delivery and usage,” meaning that firms often order raw materials well before they are used in production. If the investment in such raw materials is costly to reverse, then this investment becomes risky and at least somewhat long-lived, causing its  $q$  to respond more strongly to changes in the risk premium. Work in progress inventories, at the aggregate level, will by construction be dominated by firms producing goods that take more time to produce. Again, given the likely costs of reversing such investment, work in progress inventories will also have a  $q$  that varies significantly with the risk premium.

As in prior work, we also find no evidence that the ex ante real rate has any effect on inventories. Our results are also consistent with earlier research, reviewed by Blinder and Maccini (1991), in finding essentially no evidence of mean reversion in aggregate inventories.

Firm-level results presented below suggest this may be an aggregation issue, consistent with the findings of Blinder (1986). There is some evidence of a positive relation between inventory growth and expected sales growth.

Table 3 reports the results of regressions of longer-horizon growth in total manufacturing inventories. We examine longer horizons given existing evidence that growth rates in fixed capital investment (Lettau and Ludvigson, 2002) and employment (Chen and Zhang, 2011) appear more related to risk premiums in the long run than the short run. To do so, we reestimate the predictive regressions reported in Table 1 using sales growth rates and asset returns that are computed over the same horizon as the inventory growth being forecasted. The longer-horizon expectations implied by these predictive regressions replace the short-horizon versions used in Table 2. The other explanatory variables are unchanged.

The results are somewhat supportive of the idea that risk premiums have a greater effect over longer horizons. The coefficient on the bond risk premium steadily increases in magnitude out to four quarters and declines

**Table 3**

Aggregate inventory growth at various horizons.

In this table we report the results of regressions of aggregate inventory growth rates over several different horizons. Values in parentheses are  $t$ -statistics, computed according to Pagan (1984) except that they include a heteroskedasticity and autocorrelation adjustment. Since the observation intervals are overlapping, we set the number of lags equal to four times the length of the forecast horizon. Regressors are similar to those used in Table 2 except that expected growth in sales and expected real returns and excess returns are now also computed over long horizons. Specifically, expected sales growth is now the expectation at time  $t-1$  of growth between  $t-1$  and  $t-1+\tau$ , where  $\tau$  is the length of the forecast horizon. Expected risk premiums and real returns are cumulative over the same interval. These expectations are computed using the same predictive regressions reported in Table 1 except that the dependent variables are computed over a horizon of  $\tau$  quarters. Data are quarterly from 1958Q1 to 2010Q4. Where noted, coefficient estimates have been multiplied by 100.

Intercept ( $\times 100$ )	$\ln(N_{t-1}/Y_{t-1})$ ( $\times 100$ )	$E[\Delta \ln Y]$	$E[RF]$	$E[RBRF]$	$E[RMRF]$	Adj. $R^2$ (%)
1 Quarter						
0.25 (0.34)	0.01 (0.01)	0.33 (2.24)	0.18 (0.40)	-0.28 (-4.65)		10.78
1.93 (2.73)	2.17 (2.10)	0.06 (0.39)	0.16 (0.40)		-0.21 (-4.25)	6.86
2 Quarters						
-0.50 (-0.35)	-1.24 (-0.69)	0.59 (3.51)	0.28 (0.55)	-0.39 (-4.22)		19.86
3.35 (2.09)	3.72 (1.56)	0.22 (1.46)	0.00 (-0.01)		-0.20 (-3.58)	12.23
4 Quarters						
-1.82 (-0.46)	-3.40 (-0.72)	0.70 (2.88)	0.32 (0.56)	-0.42 (-4.55)		18.77
6.52 (2.27)	7.32 (1.69)	0.18 (1.58)	0.02 (0.08)		-0.19 (-3.66)	11.91
8 Quarters						
4.70 (1.20)	3.90 (0.77)	0.41 (2.57)	0.05 (0.17)	-0.34 (-2.91)		13.76
10.58 (2.17)	11.13 (1.79)	0.10 (0.75)	-0.48 (-1.58)		0.01 (0.11)	8.58

slightly at the eight-quarter horizon. The stock premium coefficient is only significant out to four quarters, however, and the coefficient is fairly stable over these horizons. The results imply that risk premiums predict inventory growth out at least four quarters, possibly more, with forecasting power that peaks somewhere between two and four quarters.

#### 2.4. Industry-level analysis

We next examine the behavior of inventory growth rates at the industry level. As discussed above, we have inventory data from 12 industries (based on two-digit SIC codes), and these inventories cannot be disaggregated into inputs and outputs. Six of these industries are categorized as producing nondurables (food, tobacco, paper, chemicals, petroleum products, and rubber), and six produce durables (stone/clay/glass, primary metals, fabricated metals, industrial machinery, electronic equipment, and transportation equipment).

We begin by repeating our aggregate regression specification on each industry, with the only change being that sales and inventories are now defined on the industry level. These results appear in Table 4. The table also includes several variables that we believe should be related to the riskiness of inventory investments. The first, the “GDP beta,” is simply the slope coefficient of a

regression of quarterly sales growth on quarterly growth in per capita GDP. This regression is run completely independently of our model for inventory growth. Second is the average delivery lead time, computed as the ratio of unfilled orders to shipments. Because longer lead times make it more difficult to adjust inventories by changing production, firms with longer lead times should be more sensitive to economic activity. Finally, we include the average ratio of patents to shipments as a measure of the rate of product obsolescence. An inventory that is quick to become obsolete should compound the effect of any decline in business conditions.

In regressions that use the bond market risk premium, the estimated coefficient on  $E_{t-1}[RBRF_t]$  is negative in 11 out of 12 cases but statistically significant in only seven. Five of these seven significant coefficients are found for industries producing durable goods. The coefficients on the two nonfinancial variables are usually insignificant, with the exception of a highly significant positive relation between expected petroleum sales and inventory growth. The coefficient on the ex ante real rate is significant in just two out of 12 industries, and it is positive in both cases.

In regressions that use the stock risk premium, the coefficient on  $E_{t-1}[RMRF_t]$  is positive in many nondurable industries but significantly negative for five out of the six durable goods industries and for one of the nondurable

industries. Coefficients on other regressors are broadly similar to the values estimated using  $E_{t-1}[RBRF_t]$ .

Fig. 2 plots the estimated risk premium coefficient of each industry against its GDP beta. We hypothesized that cyclicality in sales, which the GDP beta measures, is an important determinant of the riskiness of inventory investment, which makes that investment more sensitive to movements in marketwide risk premiums. Consistent with this prediction, we see a striking relation in Panel A that shows that industries with higher GDP betas tend to have more negative coefficients on  $E_{t-1}[RBRF_t]$ . Results using  $E_{t-1}[RMRF_t]$  are similar, with one exception: The estimated  $E_{t-1}[RMRF_t]$  coefficient for the primary metal industry is very positive, even though that industry's GDP beta is large. The visual blemish that results from including this industry is mitigated by the fact that neither its  $E_{t-1}[RBRF_t]$  nor  $E_{t-1}[RMRF_t]$  coefficient is significant. Thus, this particular outlier is most likely not very meaningful.

In both figures, the industrial machinery and electronics industries appear somewhat inconsistent with the generally negative relation in that their sensitivity to market risk premiums appears high relative to their low GDP betas. It is notable that both of these industries are characterized by a very high rate of technological innovation, as proxied by the ratio of patents to shipments, meaning that inventories held by firms in these industries may quickly become obsolete. Furthermore, both of these industries have long delivery lead times, implying a lack of flexibility in adjusting those inventories. Together, these factors should amplify the effects of a shock to business conditions on the level of inventories, suggesting that our beta measure may be inadequate for capturing the true riskiness of inventory investment in these industries.

To address this issue more formally, we adopt an alternative Fama and MacBeth (1973) regression approach

**Table 4**

Inventory growth regressions for individual industries.

In this table we report the results of regressions of two-digit SIC industry-level manufacturing inventory growth rates on an inventory stock measure, expected sales growth, the real riskless interest rate, and a risk premium measure. Values in parentheses are *t*-statistics, computed according to Pagan (1984) except that they include a heteroskedasticity and autocorrelation adjustment with four lags. Where noted, coefficient estimates have been multiplied by one hundred. The regressions in table are identical to those in Table 2 except that they examine total inventories at the industry level rather than aggregate manufacturing inventories. The same regressors are used except that we now use industry-level values for sales growth rates and inventory-sales ratios. The table also includes the “GDP beta,” lead time, and patents rate, which are the result of separate analyses. The GDP beta is from the regression of quarterly industry-level sales growth on GDP growth. Lead time is measured as the average ratio of unfilled orders to shipments. For the nondurable goods sector, figures for individual industries are unavailable, so we use the value computed from the nondurable aggregate. Patents measures the average yearly ratio of industry patents to shipments. Data are quarterly from 1958Q1 to 2010Q4.

	Baseline model estimates					Industry characteristics			
	$\ln(N_{t-1}/Y_{t-1})$ ( $\times 100$ )	$E[\Delta \ln Y_t]$	$E[RF_t]$	$E[RBRF_t]$	$E[RMRF_t]$	Adj. $R^2$ (%)	GDP beta	Lead time	Patents
Nondurable industries									
Food & kindred products	−1.03 (−0.55)	0.54 (3.11)	0.06 (0.14)	−0.05 (−0.46)		0.47	0.37 (1.67)	0.74	1.6
	−0.25 (−0.10)	0.09 (0.32)	−0.34 (−0.49)		0.25 (2.45)	2.37			
Tobacco products	0.87 (0.82)	0.24 (0.49)	−1.40 (−1.47)	0.16 (0.88)		1.10	0.60 (1.39)	0.74	1.6
	0.38 (0.30)	0.35 (0.59)	−1.93 (−1.74)		0.31 (2.24)	2.52			
Paper & allied products	−0.13 (−0.06)	0.04 (0.22)	0.67 (1.80)	−0.20 (−2.73)		2.49	0.86 (4.06)	0.74	8.2
	0.73 (0.21)	−0.06 (−0.30)	0.45 (1.22)		−0.04 (−0.57)	−1.05			
Chemical & allied products	4.34 (1.61)	−0.11 (−0.87)	1.34 (2.20)	−0.20 (−1.53)		1.43	1.12 (3.91)	0.74	35.0
	3.42 (0.91)	−0.10 (−0.46)	0.96 (1.29)		0.05 (0.39)	0.57			
Petroleum & coal products	−10.29 (−2.67)	1.89 (4.54)	1.73 (0.87)	−0.03 (−0.10)		4.45	1.13 (3.55)	0.74	2.9
	−10.71 (−2.89)	1.97 (2.81)	1.21 (0.65)		0.22 (0.83)	4.79			
Rubber & misc. plastics products	−4.00 (−1.97)	0.48 (3.17)	0.53 (1.14)	−0.25 (−2.86)		4.75	1.65 (4.79)	0.74	74.8
	−1.36 (−0.76)	0.31 (2.61)	0.59 (1.27)		−0.16 (−2.85)	3.86			

Table 4 (continued)

	Baseline model estimates					Industry characteristics			
	$\ln(N_{t-1}/Y_{t-1})$ ( $\times 100$ )	$E[\Delta \ln Y_t]$	$E[RF_t]$	$E[RBRF_t]$	$E[RMRF_t]$	Adj. $R^2$ (%)	GDP beta	Lead time	Patents
Durable industries									
Stone, clay, & glass products	-2.68 (-1.62)	0.19 (1.54)	1.08 (2.24)	-0.40 (-4.14)		12.73	1.94 (6.43)	1.06	33.3
	-2.19 (-1.74)	0.02 (0.18)	0.80 (2.01)		-0.13 (-2.73)	3.32			
Primary metal industries	-2.18 (-0.84)	-0.15 (-1.12)	0.29 (0.23)	-0.38 (-1.70)		3.71	3.26 (4.53)	1.99	3.6
	-5.68 (-1.58)	0.00 (0.03)	-1.00 (-0.77)		0.35 (1.48)	2.85			
Fabricated metal products	-3.52 (-2.03)	0.53 (3.18)	0.32 (0.49)	-0.35 (-4.39)		13.28	1.79 (6.83)	2.44	54.3
	-1.13 (-0.65)	0.29 (1.61)	0.39 (0.70)		-0.27 (-2.99)	11.11			
Industrial machinery	-0.45 (-0.63)	0.49 (3.96)	-0.23 (-0.38)	-0.41 (-3.96)		34.28	0.92 (4.10)	3.28	62.6
	0.35 (0.49)	0.38 (3.76)	-0.55 (-0.97)		-0.19 (-2.17)	25.39			
Electronic equipment	-0.27 (-0.34)	0.74 (6.39)	0.25 (0.43)	-0.45 (-4.56)		34.01	1.01 (3.50)	2.93	137.4
	1.00 (1.47)	0.60 (5.51)	0.11 (0.21)		-0.28 (-3.76)	28.72			
Transportation equipment	-2.47 (-1.51)	0.29 (1.65)	0.74 (0.82)	-0.41 (-2.67)		9.17	3.70 (6.49)	6.22	12.6
	0.43 (0.24)	-0.04 (-0.15)	0.82 (0.70)		-0.42 (-2.63)	10.60			

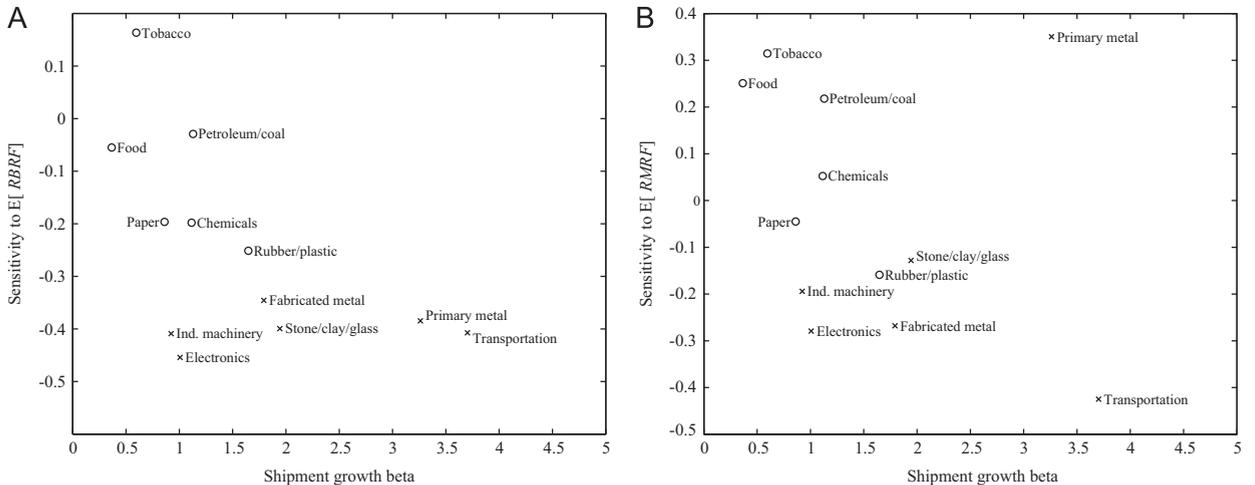


Fig. 2. Cross-sectional relationships between shipment growth betas and the sensitivity of inventory investment to the bond and stock risk premiums. This figure shows the relation between the slope coefficient of a regression of quarterly industry sales growth rates on GDP growth and the sensitivity of inventory investment to a risk premium. In Panel A, this sensitivity is measured by the coefficient on  $E[RBRF]$  in the regressions of inventory growth reported in Table 4. In Panel B, it is measured by the coefficient on  $E[RMRF]$  from Table 4. All values are computed using data from 1958Q1 to 2010Q4. Industries that primarily produce nondurables are identified by an “o,” while durable-producing industries are marked with an “x.”

that jointly analyzes all 12 industries. The goal is to see if there are interaction effects between our estimated risk premiums and various measures of industry-level risk,

such that high-risk industries invest particularly less in inventories when risk premiums are high. This suggests a regression that is similar to (1) but that adds a risk proxy

to the risk premium term:

$$\Delta \ln N_{i,t} = b_0 + b_1 \ln(N_{i,t-1}/Y_{i,t-1}) + b_2 E_{t-1}[\Delta \ln Y_{i,t}] \\ + b_3 E_{t-1}[RF_t] + b_4 E_{t-1}[RP_t] \times \text{Risk}_i + \epsilon_{i,t}.$$

In the Fama-MacBeth framework, however, second-pass regressions cannot include either  $E_{t-1}[RF_t]$  or  $E_{t-1}[RP_t]$ , since these are constant across industries and will therefore be absorbed into other regression coefficients.

We therefore run the simpler following regression for each quarter<sup>3</sup>:

$$\Delta \ln N_{i,t} = \lambda_{0,t} + \lambda_{1,t} \ln(N_{i,t-1}/Y_{i,t-1}) \\ + \lambda_{2,t} \Delta \ln Y_{i,t-1} + \lambda_{3,t} \text{Risk}_i + \epsilon_{i,t}. \quad (2)$$

If there is an interaction between the risk measure and the risk premium, then the effect of  $E_{t-1}[RP_t]$  will be absorbed into the estimates of  $\lambda_{3,t}$ . We may therefore test for this effect in the “third pass” regression

$$\hat{\lambda}_{3,t} = b_0 + b_1 E_{t-1}[RP_t] + \epsilon_t, \quad (3)$$

where the expectation is again proxied with fitted values from the regressions in Table 1.<sup>4</sup>

We estimate (2) and (3) using four different industry risk proxies, namely the GDP beta, the patent/sales ratio, the new order lead time, and a durable industry dummy variable. The results of estimating (3) are in Table 5. We do not report the results of the second-pass regression (2) because they are not informative about risk premium effects.

Table 5 reports modest but consistent evidence that the risk premium coefficient  $b_1$  in (3) is negative. This implies that high-risk industries see larger declines in inventory growth when aggregate risk premiums rise. The results further suggest that the characteristics of the goods produced, in particular, whether they are durables or nondurables and whether the industry has a high rate of technological innovation, may proxy for inventory risk as well as or even better than the cyclical nature of the industry's sales.

## 2.5. Firm-level regressions

Our firm-level analysis differs in its use of proxies for risk premiums based on implied costs of capital (ICC) rather than fitted values from predictive return regressions. We use three different ICC measures, each of which is constructed from current equity prices and projections of future firm earnings. Our primary measure, which was proposed by Gebhardt, Lee, and Swaminathan (2001), uses analyst forecasts to proxy for expected future earnings. The others, due to Hou, van Dijk, and Zhang (2012) and Wu and Zhang (2011), use regression models to construct forecasts of

<sup>3</sup> Using lagged sales growth rather than a fitted value for  $E_{t-1}[\Delta \ln Y_{i,t}]$  is for convenience, as it is unclear how the Pagan (1984) approach generalizes to the Fama-MacBeth setting. We note that using lagged sales growth instead of  $E_{t-1}[\Delta \ln Y_{i,t}]$  in Table 4 had no noticeable effect on the coefficients on other variables.

<sup>4</sup> An alternative method would have been to follow Ferson and Harvey (1991) and simply regress  $\hat{\lambda}_{3,t}$  on lagged predictive variables directly. Our approach differs in that only a specific linear combination of predictive variables, namely, that which best forecasts excess returns, is used as a regressor. We believe that limiting the possible scope of predictability puts somewhat greater discipline on our analysis.

**Table 5**

Industry-level Fama-MacBeth regressions.

This table reports the results of regressions in which measures of risk premiums are used to predict selected coefficients from a Fama-MacBeth second-pass regression. Explanatory variables in the second-pass regression include the industry-level inventory stock measure  $\ln(N_{i,t-1}/Y_{i,t-1})$ , the lagged industry sales growth rate ( $\Delta \ln Y_{i,t-1}$ ), and one of four different proxies of industry riskiness. These risk proxies consist of the beta in a regression of industry sales growth on GDP growth, the average lead time for new orders for that industry, the average ratio of patents to sales in the industry, and a dummy variable indicating if the industry is a durable goods producer. Defining  $\hat{\lambda}_t$  as the Fama-MacBeth second-pass coefficient corresponding to a given risk proxy, we run the regression

$$\hat{\lambda}_t = b_0 + b_1 E_{t-1}[RP_t] + \epsilon_t,$$

where  $RP_t$  is either  $RMRP_t$  or  $RBRP_t$ . The table reports estimates for the intercept and the slope coefficient for both risk premium proxies and all four risk measures. Values in parentheses are  $t$ -statistics, computed according to Pagan (1984) except that they include a heteroskedasticity and autocorrelation adjustment with four lags. Data are quarterly from 1958Q1 to 2010Q4.

	Intercept	E[ $RBRP_t$ ]	Adj. $R^2$ (%)	Intercept	E[ $RMRP_t$ ]	Adj. $R^2$ (%)
GDP beta	0.00 (3.49)	-0.15 (-2.21)	3.18	0.00 (3.61)	-0.11 (-2.20)	2.71
Lead time	0.03 (4.05)	-0.32 (-0.66)	0.05	0.04 (3.74)	-0.83 (-1.97)	5.23
Patents	0.10 (4.17)	-1.65 (-1.43)	1.01	0.13 (3.98)	-2.67 (-2.68)	5.92
Durable dummy	0.01 (4.40)	-0.20 (-2.26)	2.91	0.01 (4.05)	-0.24 (-2.59)	7.48

future earnings. Earnings are forecasted directly in the case of Hou, van Dijk, and Zhang (2012). In Wu and Zhang (2011), a regression is used to forecast firm ROE, which is then converted to an earnings-level forecast. Wu and Zhang (2011) argue that their approach should avoid problems associated with the nonstationarity of earnings levels. Our decision to use implied cost of capital measures is primarily for tractability—since there is no generally accepted model of expected firm returns, constructing regression-based proxies like those used in our aggregate inventory analysis would be challenging and arbitrary.

Our baseline specification, estimated using annual data, is similar to those used previously:

$$\Delta \ln N_{i,t} = \lambda_0 + \lambda_1 \ln(N_{i,t-1}/Y_{i,t-1}) \\ + \lambda_2 \Delta \ln Y_{i,t-1} + \lambda_3 ICC_{i,t-1} + \epsilon_{i,t}, \quad (4)$$

where  $ICC_{i,t-1}$  is implied cost of capital that would be observed prior to the start of year  $t$ .

Earlier work on inventory investment examines the effects of financing constraints, and we add key variables from these papers to some specifications as control variables.<sup>5</sup> Kashyap, Lamont, and Stein (1994) find that

<sup>5</sup> Kashyap, Stein, and Wilcox (1993) find that a proxy for bank loan supply helps predict aggregate inventory growth. Studies examining inventory patterns and financial constraints in the cross section of firms include Gertler and Gilchrist (1994), Kashyap, Lamont, and Stein (1994), and Carpenter, Fazzari, and Petersen (1998). All four of these papers show that greater financing constraints, whether in the cross section or the time series, depress inventory investment.

**Table 6**

Firm-level regressions.

This table reports estimates and t-statistics from firm-level regressions of annual inventory growth on various lagged explanatory variables. Regressions 1–12 use the Fama-MacBeth approach, while 13 and 14 are panel regressions with firm fixed effects. Standard errors from Fama-MacBeth regressions are computed using the method of Newey and West (1987) with one lag. Panel regression standard errors account for conditional heteroskedasticity but not autocorrelation, and in addition are clustered by date. Explanatory variables include the firm's lagged log ratio of inventory to sales, past sales growth, an equity cost of capital measure, log firm size, the ratio of cash flow (CF) to assets, and the inverse coverage ratio. Except for regressions 9–12, the cost of capital measure is computed using the approach of Gebhardt, Lee, and Swaminathan (2001), which results in 38,632 firm-year observations between 1977 and 2010. Regressions 9 and 10 use the cost of capital measure of Hou, van Dijk, and Zhang (HVDZ, 2012), available for 50,204 observations between 1972 and 2010. Regressions 11 and 12 use the measure from Wu and Zhang (WZ, 2011), which has 49,834 observations between 1972 and 2010. Where noted, coefficient estimates have been multiplied by 100.

#	Intercept	$\ln(N_{t-1}/Y_{t-1})$	$\Delta \ln(Y_{t-1})$	$E[R_t]$	Size <sub>t-1</sub> ( $\times 100$ )	CF/Assets	Coverage ( $\times 100$ )	Liquidity	$\Delta \ln(N_{t-1})$ ( $\times 100$ )	R <sup>2</sup> (%)	Notes
1	0.10 (8.52)	-0.28 (-13.16)	0.22 (12.80)							2.92	
2	0.18 (13.03)	-0.28 (-12.93)	0.21 (12.73)	-0.78 (-8.54)						3.45	
3	0.10 (6.75)	-0.26 (-11.65)	0.20 (11.31)	-0.40 (-3.83)				0.37 (9.60)		4.40	
4	0.23 (8.54)	-0.29 (-12.11)	0.21 (12.25)	-0.87 (-9.24)	-0.58 (-2.59)				-0.59 (-0.57)	3.47	
5	0.11 (4.14)	-0.26 (-11.07)	0.20 (10.96)	-0.41 (-3.84)	-0.11 (-0.47)			0.38 (9.89)	-0.43 (-0.43)	4.38	
6	0.07 (4.49)	-0.22 (-9.40)	0.19 (11.03)	-0.36 (-3.78)		0.23 (7.04)	-1.35 (-1.43)	0.39 (11.17)		5.12	
7	0.05 (2.55)	-0.22 (-8.86)	0.20 (11.01)		-0.33 (-1.68)	0.27 (8.38)	-1.64 (-1.83)	0.40 (11.48)	-0.54 (-0.51)	5.00	
8	0.11 (4.63)	-0.22 (-9.30)	0.20 (10.83)	-0.45 (-4.45)	-0.58 (-2.79)	0.25 (7.34)	-1.47 (-1.51)	0.38 (10.95)	-0.69 (-0.67)	5.16	
9	0.15 (9.52)	-0.32 (-11.53)	0.16 (9.64)	-0.51 (-7.76)						3.01	HVDZ cost of capital
10	0.10 (4.24)	-0.26 (-9.43)	0.15 (8.48)	-0.38 (-6.10)	-0.38 (-2.19)	0.31 (6.93)	-0.91 (-1.45)	0.32 (11.89)	-1.50 (-1.57)	4.53	HVDZ cost of capital
11	0.16 (8.15)	-0.35 (-12.48)	0.16 (9.54)	-0.63 (-5.74)						2.83	WZ cost of capital
12	0.05 (2.23)	-0.27 (-9.59)	0.15 (8.62)	-0.29 (-2.66)	0.10 (0.61)	0.31 (7.16)	-1.12 (-1.82)	0.33 (12.19)	-1.27 (-1.36)	4.50	WZ cost of capital
13		-0.37 (-7.73)	0.16 (9.60)	-0.83 (-6.25)	-1.07 (-3.48)	0.26 (7.00)	-1.93 (-3.68)	0.37 (9.47)	-0.40 (-0.32)	5.02	Panel with industry fixed effects
14		-0.65 (-9.40)	0.14 (9.02)	-0.81 (-4.83)	-1.00 (-1.44)	0.30 (6.40)	-2.35 (-3.72)	0.69 (18.47)	-5.23 (-4.66)	18.29	Panel with firm fixed effects

greater liquidity, defined as the ratio of cash and short-term investments to total assets, forecasts higher inventory growth. Carpenter, Fazzari, and Petersen (1998) argue that both the ratio of cash flow to assets and interest rate coverage are important determinants. We include these variables, in addition to log firm size and lagged inventory growth, in our most general specification.

Including variables related to financing constraints ensures that any cost of capital effect found is not merely a proxy for the strength of those constraints. As shown theoretically by Livdan, Saprizza, and Zhang (2009), binding financing constraints should lead to a higher firm cost of capital. We would therefore like to distinguish between an inventory/cost of capital relationship that is the result of a financing constraint effect, which has been documented previously, to one that is based on standard  $q$  theory. We can be more confident of the latter

explanation if the cost of capital effect survives the inclusion of various financing constraint proxies.

We estimate several versions of the model using Fama-MacBeth regressions. Most specifications use the Gebhardt, Lee, and Swaminathan (2001) implied cost of capital. While this is perhaps the most widely used method, it relies on analyst forecast data and therefore cannot be applied to a large number of primarily small firms. We therefore use the measures of Hou, van Dijk, and Zhang (2012) and Wu and Zhang (2011), which are available for more than 25% more firm-years over a longer sample, as robustness checks. As an additional check, we also estimate our most general specification using panel data regressions with industry or firm fixed effects.

The results, in Table 6, show strong evidence demonstrating the importance of risk premiums. Across a variety of specifications, with two different cost of capital measures, and using two different regression methods, the

**Table 7**

Inventory-sorted portfolio return means and alphas.

This table reports on the performance of portfolios formed on the basis of past inventory growth ( $\Delta \ln N$ ), with and without industry adjustments. Values shown are computed from monthly returns and then annualized. Numbers in parentheses are  $t$ -statistics, computed using the Newey and West (1987) procedure with three lags. In June of each year, we sort firms into five value-weighted portfolios based on past annual firm inventory growth and use these portfolio returns to compute excess return means, CAPM alphas, and Fama and French (1993) alphas. The leftmost set of results is computed from portfolios sorted on the basis of unadjusted inventory growth rates. The middle three columns are computed from portfolios formed on the basis of industry-adjusted inventory growth, in which we subtract the value-weighted average inventory growth rate of the firm's three-digit SIC industry from that firm's own inventory growth. The differences between these two sets of portfolios are described in the rightmost three columns. The top panel of the table includes all firms in our sample, while the bottom panel includes only those firms in the manufacturing sector (whose two-digit SIC codes are listed in Table A1). The sample is from July 1966 to December 2010.

Portfolio	Portfolios formed on unadjusted inventory growth			Portfolios formed on industry-adjusted inventory growth			Difference		
	Mean return	CAPM alpha	FF alpha	Mean return	CAPM alpha	FF alpha	Mean return	CAPM alpha	FF alpha
All firms									
Low $\Delta \ln N$	9.26 (3.18)	3.64 (3.20)	3.26 (2.85)	7.49 (2.65)	1.99 (1.81)	1.78 (1.62)	1.76 (2.15)	1.65 (2.01)	1.49 (1.91)
2	6.67 (2.60)	1.59 (2.14)	1.08 (1.52)	6.20 (2.41)	1.03 (1.46)	0.96 (1.41)	0.47 (0.67)	0.56 (0.79)	0.12 (0.16)
3	5.59 (2.52)	1.01 (1.15)	0.75 (0.92)	6.13 (2.71)	1.46 (1.79)	1.26 (1.65)	-0.54 (-0.98)	-0.45 (-0.82)	-0.51 (-0.89)
4	5.83 (2.28)	0.70 (0.92)	1.57 (2.20)	5.38 (2.18)	0.41 (0.54)	1.24 (1.68)	0.45 (0.71)	0.29 (0.47)	0.33 (0.51)
High $\Delta \ln N$	3.53 (1.07)	-2.59 (-2.11)	-0.90 (-0.87)	4.36 (1.32)	-1.82 (-1.49)	-0.37 (-0.36)	-0.83 (-1.43)	-0.77 (-1.35)	-0.53 (-0.93)
Low-High	5.73 (3.68)	6.23 (4.07)	4.16 (2.84)	3.13 (2.14)	3.81 (2.67)	2.14 (1.64)	2.60 (2.35)	2.42 (2.21)	2.02 (1.92)
Manufacturing firms only									
Low $\Delta \ln N$	9.49 (3.07)	3.82 (2.51)	3.75 (2.48)	8.37 (2.92)	2.87 (2.23)	2.79 (2.13)	1.12 (1.27)	0.95 (1.13)	0.96 (1.12)
2	7.49 (2.87)	2.55 (2.45)	1.84 (1.81)	6.52 (2.63)	1.50 (1.69)	1.18 (1.32)	0.96 (1.00)	1.05 (1.08)	0.66 (0.69)
3	6.24 (2.80)	1.69 (1.59)	1.52 (1.50)	6.24 (2.77)	1.72 (1.55)	1.72 (1.65)	-0.01 (-0.01)	-0.03 (-0.06)	-0.20 (-0.34)
4	5.28 (2.02)	0.14 (0.14)	1.39 (1.59)	5.53 (2.12)	0.35 (0.35)	1.53 (1.71)	-0.25 (-0.35)	-0.21 (-0.29)	-0.14 (-0.20)
High $\Delta \ln N$	5.20 (1.50)	-1.16 (-0.72)	1.21 (0.90)	5.45 (1.57)	-0.94 (-0.61)	1.48 (1.17)	-0.25 (-0.46)	-0.22 (-0.40)	-0.26 (-0.47)
Low-High	4.30 (2.14)	4.98 (2.53)	2.54 (1.34)	2.92 (1.72)	3.81 (2.31)	1.31 (0.87)	1.38 (1.20)	1.17 (1.07)	1.22 (1.09)

cost of capital coefficient is consistently negative, with  $t$ -statistics below  $-3$  in every case but one. The magnitude of the coefficient is somewhat variable, depending both on the control variables included and the method used to compute the implied cost of capital, but it does not fluctuate excessively.

A number of the control variables are significant as well. Mean reversion, as measured by the coefficient on the lagged inventory/sales ratio, is faster for firms than it is at the aggregate level. The liquidity measure of Kashyap, Lamont, and Stein (1994) is highly significant in every case, as is the ratio of cash flow to assets. Interest rate coverage is insignificant in all regressions except for the panel regressions with fixed effects. Size and lagged inventory growth have comparatively little effect.

In sum, a higher cost of capital at the firm level reduces inventory growth. This is neither purely a time series or cross-sectional effect given that we obtain this result both in a panel regression with firm fixed effects and in a Fama-MacBeth regression, with its implicit time fixed effects.

## 2.6. Portfolios

Prior literature (e.g., Thomas and Zhang, 2002; Belo and Lin, 2012) has observed that portfolios formed on the basis of past inventory growth display significant variation in expected returns. We replicate this analysis by computing value-weighted portfolio returns in which firms are assigned to quintile portfolios each July based on their inventory growth rate as of the last fiscal year

and held until June of the following year. We also examine portfolios formed on the basis of industry-adjusted inventory growth, where we subtract the value-weighted average inventory growth rate of the firm's three-digit SIC industry from that firm's own inventory growth. If the relation between inventory growth and average returns contains an industry effect, then the return spread from portfolios formed on industry-adjusted inventory growth should be smaller.<sup>6</sup>

Consistent with prior work, the results in Table 7 show that the returns of low inventory growth firms exceed those of high growth firms by 5.73% per year. This spread is not explained by either the Capital Asset Pricing Model (CAPM) or the Fama-French model, which produce annualized alpha spreads of 6.23% and 4.16%, respectively. While returns and CAPM alphas are both fairly monotonically related to inventory growth, there is relatively little spread in the returns of portfolios 2–4, representing the middle 60% of the market, so the spread seems to come mainly from the behavior of portfolios 1 and 5.

The middle columns of Table 7 report similar statistics for portfolios formed on industry-adjusted inventory growth. The results show that industry adjustment reduces the spread between high and low inventory growth portfolios by a little less than half. In other words, the relationship between inventory growth and the cost of capital is partly due to a similar relationship at the industry level. This industry effect can be measured by subtracting the returns on portfolios based on adjusted returns from those based on unadjusted returns. Means of these differences appear in the last three columns of the table. The table shows that industry effects are sizeable and significant both in excess returns and CAPM alphas.

In the bottom half of Table 7 we examine the sample of manufacturing firms separately. We do so because those are the ones that are represented in the M3 database used for the aggregate- and industry-level results. In addition, they represent a set of firms in somewhat similar industries. As a result of focusing on manufacturing firms, there is less between-industry variation, and this leads to smaller differences in the returns of high and low inventory growth firms. The spread in returns drops to 4.30% and the CAPM alpha spread drops to 4.98%, both of which remain significant. Performing industry adjustments to the manufacturing firm reduces both of these numbers by less than a third.

Having established that there is an industry-related component to the returns of high and low inventory growth firms, we now examine the industry composition of these portfolios. We examine several industry-level characteristics. Three of these are constructed with aggregate industry sales and inventories, namely the GDP beta (the slope of the regression of industry sales growth on GDP growth), the volatility of industry sales growth, and the volatility of industry inventory growth. We also look at a manufacturing industry dummy variable and, for the

**Table 8**

Average industry characteristics of inventory-sorted portfolios.

This table reports average industry characteristics of portfolios formed on the basis of past inventory growth. We compute growth rates of total sales and inventories across all firms in each three-digit SIC industry. These growth rates are used to calculate betas of the regression of inventory sales growth on GDP growth as well as standard deviations of industry sales and inventory growth rates. Other industry characteristics include a dummy variable indicating if the firm is in the manufacturing sector and, for manufacturing firms, the four risk proxies used in Table 5. We assign to each firm its industry characteristics and compute value-weighted averages for each portfolio in each year. The table reports portfolio time series means. Stars denote means that are significantly different from portfolio 3, where one, two, and three stars denote significance at the 10%, 5%, and 1% levels, respectively, and where significance tests use Newey and West (1987) standard errors with two lags.

Portfolio	All firms			
	GDP beta	SD of $\Delta N$ (%)	SD of $\Delta S$ (%)	Manufacturing dummy
1	1.42***	11.5***	8.9**	0.52***
2	1.33	10.6***	8.8**	0.64
3	1.31	10.1	8.1	0.67
4	1.33	10.4**	8.0	0.59***
5	1.47***	11.5***	8.7**	0.51***
Portfolio	Manufacturing firms only			
	GDP beta	Durable dummy	Lead time	Patents
1	1.43***	0.47***	2.16***	37.8*
2	1.27	0.37	1.90	32.8
3	1.26	0.33	1.82	31.8
4	1.30	0.36	1.82	37.3***
5	1.49***	0.52***	2.15***	48.6***

sample of manufacturing firms, the three other risk proxies (besides GDP beta) examined in Table 5. One value of each characteristic is computed for each three-digit SIC industry, and that value is then assigned to each firm within that industry. Table 8 reports the average values of each characteristic for the five portfolios formed on the basis of past inventory growth.

In short, firms in the extreme portfolios 1 and 5 tend to come from industries that are more procyclical and more volatile, both in terms of their sales and (almost by construction) inventories. The extreme portfolios also tend to have fewer manufacturing firms than the middle portfolios. In the sample of manufacturing firms, for which we have data on all four risk proxies, we find that the extreme portfolios are more likely to consist of firms in industries that produce durable goods, require longer lead times, and have a higher concentration of patent activity. All of these results are consistent with our findings from industry-level regressions.

We conclude that the spread between high and low inventory growth firms has an important industry component. Nonmanufacturing firms and firms in industries in which inventory investment is likely to be more risky are overrepresented in the extreme portfolios. These results suggest that industry-level heterogeneity plays an important role in the relation between inventory investment and the cost of capital.

<sup>6</sup> We have also examined the industry-adjusted returns on portfolios formed on the basis of unadjusted inventory growth. This alternative notion of industry adjustment results in a very similar decomposition of returns into industry- and firm-specific components.

### 3. Model

The purpose of our theoretical model is to investigate the relationship between inventory investment and risk premiums at the firm and aggregate levels. The model economy is populated with competitive firms producing a homogeneous good using capital and labor. As in Kydland and Prescott (1982) and Christiano (1988), firms use two types of capital goods, fixed capital (equipment and structures) and inventories, and both are subject to convex adjustment costs. Labor is assumed freely adjustable. All risk in the economy is generated from productivity shocks that include aggregate- and firm-level components. We pair this model of production with an exogenous pricing kernel, following Berk, Green, and Naik (1999), Zhang (2005), and Gomes and Schmid (2010), and an exogenously specified stochastic wage rate process, as in Bazzdrusch, Belo, and Lin (2009).

#### 3.1. Firms

There are many firms that produce a homogeneous good using labor, fixed capital, and inventories. Firms are subject both to aggregate productivity shocks and to different firm-level productivity shocks.

The production function for firm  $i$  is given by

$$Y_{i,t} = F(A_t, Z_{i,t}, K_{i,t}, N_{i,t}, L_{i,t}) \\ = A_t Z_{i,t} ((1-s)K_{i,t}^{-\nu} + sN_{i,t}^{-\nu})^{-\alpha_C/\nu} L_{i,t}^{\alpha_L}. \quad (5)$$

The production function follows the form studied in Kydland and Prescott (1982) and Christiano (1988).  $K_{i,t}$  and  $N_{i,t}$  denote the levels of fixed capital and inventory stock for firm  $i$  at the beginning of period  $t$ . The elasticity of substitution between fixed capital and inventory is constant, with the value  $1/(1+\nu)$ . The two capital goods become perfect substitutes as  $\nu \rightarrow -1$  and perfect complements as  $\nu \rightarrow \infty$ . Taking the limit as  $\nu \rightarrow 0$  yields the Cobb-Douglas specification.  $\alpha_L$ ,  $\alpha_C$ , and  $\alpha_L + \alpha_C$  are each between zero and one. Finally,  $L_{i,t}$  denotes the labor used in production by firm  $i$  during period  $t$ .

Aggregate productivity is denoted by  $a_t = \ln(A_t)$ .  $a_t$  has a stationary and monotone Markov transition function denoted by  $p_a(a_{t+1}|a_t)$ , and follows the autoregressive (AR) process:

$$a_{t+1} = \rho_a a_t + \varepsilon_{t+1}^a, \quad (6)$$

where  $\varepsilon_{t+1}^a \sim \text{i.i.d. } N(0, \sigma_a^2)$ . Firm-specific productivity,  $z_{i,t} = \ln(Z_{i,t})$ , follows the same type of AR process:

$$z_{i,t+1} = \rho_z z_{i,t} + \varepsilon_{i,t+1}^z, \quad (7)$$

where  $\varepsilon_{i,t+1}^z \sim \text{i.i.d. } N(0, \sigma_z^2)$ . We assume that  $\varepsilon_{i,t}^z$  and  $\varepsilon_{j,t}^z$  are uncorrelated for all  $i \neq j$  and that both are uncorrelated with  $\varepsilon_t^a$ .

The capital accumulation rules are

$$K_{i,t+1} = (1-\delta_K)K_{i,t} + I_{i,t}^K, \\ N_{i,t+1} = (1-\delta_N)N_{i,t} + I_{i,t}^N, \quad (8)$$

where  $I_{i,t}^K$  and  $I_{i,t}^N$  denote investment in fixed capital and inventories, respectively.  $\delta_K$  denotes the depreciation rate of installed fixed capital and  $\delta_N$  denotes the depreciation rate of inventories. We assume that fixed capital

depreciates more slowly than inventories, so that  $\delta_N > \delta_K$ . This is consistent with the average fixed capital depreciation rates from the Bureau of Economic Analysis and the non-interest inventory carrying cost estimated by inventory management experts.

Any investment in fixed capital or inventories is subject to a convex adjustment cost, either  $g_{i,t}^K$  and  $g_{i,t}^N$ . These take the quadratic form:

$$g_K(I_{i,t}^K, K_{i,t}) = \frac{1}{2} \zeta_K \left( \frac{I_{i,t}^K}{K_{i,t}} - \delta_K \right)^2 K_{i,t} \quad (9)$$

$$g_N(I_{i,t}^N, N_{i,t}) = \frac{1}{2} \zeta_N \left( \frac{I_{i,t}^N}{N_{i,t}} - \delta_N \right)^2 N_{i,t}, \quad (10)$$

where  $\zeta_K, \zeta_N > 0$ . It is widely accepted in the literature that inventory investment is more easily adjusted than fixed capital. Carpenter, Fazzari, and Petersen (1994), for example, characterize inventories as a liquid, readily reversible investment with low adjustment costs. We would therefore expect that  $\zeta_K > \zeta_N$ , which is confirmed in our calibration. We note that for both types of capital, firms incur no adjustment cost when net investment is zero, i.e., when the firm replaces its depleted fixed capital or inventory stock and maintains its capital level.

Firms are equity financed and face a perfectly elastic supply of labor at a given stochastic equilibrium real wage rate  $W_t$ , as in Bazzdrusch, Belo, and Lin (2009). The equilibrium wage rate, given by

$$W_t = \exp(\omega a_t) \quad (11)$$

is assumed to be increasing with aggregate productivity, with  $0 < \omega < 1$  determining the sensitivity of the relation.<sup>7</sup> Hiring decisions are made after firms observe productivity shocks, and labor is adjusted freely. Hence, the marginal product of labor for each firm equals the wage rate:

$$F_{L,t} = F_L(A_t, Z_{i,t}, K_{i,t}, N_{i,t}, L_{i,t}) \\ = W_t. \quad (12)$$

The firm's dividend to shareholders is equal to

$$D_{i,t} = Y_{i,t} - [I_{i,t}^K + I_{i,t}^N + g_{i,t}^K + g_{i,t}^N] - W_t L_{i,t}. \quad (13)$$

At each date  $t$ , firms choose  $\{I_{i,t}^K, I_{i,t}^N, L_{i,t}\}$  to maximize the net present value of their expected dividend stream, which is the firm value:

$$V_t = \max_{\{I_{i,t}^K, I_{i,t}^N, L_{i,t}\}} E_t \left[ \sum_{k=0}^{\infty} M_{t,t+k} D_{i,t+k} \right], \quad (14)$$

subject to (5)–(13), where  $M_{t,t+k}$  is the stochastic discount factor between time  $t$  and  $t+k$ .  $V_t$  is the cum-dividend value of the firm.

<sup>7</sup> With competitive labor markets, wage equals the value of the marginal product of labor. In general equilibrium with a representative firm, the marginal product of labor is  $mpl = \exp(a_t) \alpha_L L^{\alpha_L - 1} K^{\alpha_C}$ . Hence, wages are a function of aggregate productivity, total labor force, and the capital stock used in production. Here, we abstract from aggregate labor and capital, and model wages as a function of aggregate productivity.

The first-order conditions for the firm's optimization problem leads to the pricing equations:

$$1 = \iint M_{t,t+1} R_{i,t+1}^K p_{z_i}(z_{i,t+1} | z_{i,t}) p_a(a_{t+1} | a_t) dz_i da, \quad (15)$$

$$1 = \iint M_{t,t+1} R_{i,t+1}^N p_{z_i}(z_{i,t+1} | z_{i,t}) p_a(a_{t+1} | a_t) dz_i da, \quad (16)$$

where the returns to investment are given by

$$R_{i,t+1}^K = \frac{F_{K_{i,t+1}} + (1 - \delta_K) q_{i,t+1}^K + \frac{1}{2} \zeta_K \left( \left( \frac{I_{i,t+1}^K}{K_{i,t+1}} \right)^2 - \delta_K^2 \right)}{q_{i,t}^K} \quad (17)$$

$$R_{i,t+1}^N = \frac{F_{N_{i,t+1}} + (1 - \delta_N) q_{i,t+1}^N + \frac{1}{2} \zeta_N \left( \left( \frac{I_{i,t+1}^N}{N_{i,t+1}} \right)^2 - \delta_N^2 \right)}{q_{i,t}^N} \quad (18)$$

and where

$$F_{K_{i,t}} = F_K(A_t, Z_{i,t}, K_{i,t}, N_{i,t}, L_{i,t}),$$

$$F_{N_{i,t}} = F_N(A_t, Z_{i,t}, K_{i,t}, N_{i,t}, L_{i,t}).$$

Tobin's  $q$ , the consumption good value of a newly installed unit of fixed capital and inventories, are

$$q_{i,t}^K = 1 + \zeta_K \left( \frac{I_{i,t}^K}{K_{i,t}} - \delta_K \right), \quad (19)$$

$$q_{i,t}^N = 1 + \zeta_N \left( \frac{I_{i,t}^N}{N_{i,t}} - \delta_N \right). \quad (20)$$

The pricing Eqs. (15) and (16) establish a link between the marginal costs and benefits of investing in fixed capital and inventories. The terms in the denominator of the right-hand side of the equations,  $q_{i,t}^K$  and  $q_{i,t}^N$ , measure the marginal cost of investing in fixed capital and inventories, respectively. The terms in the numerator represent the discounted marginal benefit of investing. The firm optimally chooses  $I_{i,t}^K$  and  $I_{i,t}^N$  such that the marginal cost of investing equals the discounted marginal benefit.

The firm's gross return is defined as<sup>8</sup>

$$R_{t+1}^S = \frac{V_{t+1}}{V_t - D_t}.$$

### 3.2. The stochastic discount factor

Following Berk, Green, and Naik (1999) and Zhang (2005), we directly parameterize the pricing kernel without explicitly modeling the consumer's problem.

Specifically, we assume that the pricing kernel is given by

$$\ln M_{t+1} = \ln \beta - \gamma_t \varepsilon_{t+1}^a - \frac{1}{2} \gamma_t^2 \sigma_a^2,$$

$$\ln \gamma_t = \gamma_0 + \gamma_1 a_t,$$

where  $\beta, \gamma_0 > 0$ , and  $\gamma_1 < 0$  are constant parameters.

Our model shares many similarities with Zhang (2005).  $M_{t+1}$ , the stochastic discount factor from time  $t$  to  $t+1$ , is driven by  $\varepsilon_{t+1}^a$ , the shock to the aggregate productivity process in period  $t+1$ . The volatility of  $M_{t+1}$  is time-varying, driven by the  $\gamma_t$  process. As in Zhang, this volatility takes higher values following business cycle contractions and lower values following expansions, resulting in a countercyclical price of risk.<sup>9</sup>

Two differences with Zhang (2005) are worth noting. One is that the riskless rate is constant in our specification. This follows the inclusion of the term  $-\frac{1}{2} \gamma_t^2 \sigma_a^2$  in the pricing kernel. This ensures that the pricing kernel has a constant expectation and implies that the riskless rate is equal to  $-\ln \beta$  in every period. As a result,  $\gamma_0$  and  $\gamma_1$  only affect the market risk premium, making it easier to interpret the effects of changing these parameters in our calibrations. The second difference is the exponential rather than linear specification of  $\gamma_t$ . The linear specification of  $\gamma_t$  in Zhang (2005) implies that there exists a value of  $a_t$  above which  $\gamma_t < 0$ , implying a region in which the risk premium is negative. While some values of the parameters of the pricing kernel and the productivity process will result in this region being reached with low probability, the exponential form allows greater flexibility in parameter choice since  $\gamma_t > 0$  regardless of the parameter values.

### 3.3. Calibration

Solving our model generates solutions for firms' investment and hiring decisions as functions of the state variables, which are the aggregate- and firm-level productivity and the fixed capital and inventories of the firms. Since the stochastic discount factor and the wages are specified exogenously, the solution does not require aggregation. Hence, the distribution of the capital stock, a high-dimensional object, is not in the state space. This feature of the model simplifies the solution of the model significantly. Our primary interest is understanding the relationship between inventory investment and the cost of capital, and specifically, the risk premium component of the cost of capital. Given that our pricing kernel implies a constant interest rate, changes in the cost of capital in the model are due entirely to fluctuating risk premiums.

We calibrate the model at quarterly frequency, but report annualized moments to match annualized

<sup>8</sup> We do not assume constant returns to scale in the production function; i.e.,  $\alpha_L + \alpha_C \in (0, 1)$ . In the presence of constant returns to scale, firm return would be equivalent to the weighted average of returns to fixed and inventory investment,  $R_{t+1}^K$  and  $R_{t+1}^N$ , where weights are the shares of fixed capital and inventories in the firm's total capital stock. With slightly decreasing returns to scale, firm returns slightly diverge from the weighted average of investment returns.

<sup>9</sup> A countercyclical price of risk is endogenously derived in Campbell and Cochrane (1999) from time-varying risk aversion; in Barberis, Huang, and Santos (2001) from loss aversion; in Constantinides and Duffie (1996) from a time-varying cross-sectional distribution of labor income; in Guvenen (2009) from limited participation; in Bansal and Yaron (2004) from time-varying economic uncertainty, and in Piazzesi, Schneider, and Tuzel (2007) from time-varying consumption composition risk.

**Table 9**

Model parameter values fixed across calibrations.

This table reports the values of parameters that are fixed across all calibrations. Parameters of the production function, namely  $\alpha_C$  and  $\alpha_L$ , are roughly equal to the estimates in Imrohorglu and Tuzel (2011), as are the firm-level productivity parameters  $\rho_z$  and  $\sigma_z$ . The depreciation parameters  $\delta_K$  and  $\delta_N$  are approximate midpoints of the values assumed or estimated in other papers. The aggregate productivity parameters  $\rho_a$  and  $\sigma_a$  are from King and Rebelo (1999). The pricing kernel parameters  $\beta$  and  $\gamma_0$  are chosen to match the average annual riskless rate (1.14%) and Sharpe ratio (36.9%) measured from the data used in our empirical section. The wage sensitivity parameter  $\omega$  is from Bazdresch, Belo, and Lin (2009). Parameters are reported on a quarterly basis.

Parameter	Description	Value
$\alpha_C$	Capital share	0.30
$\alpha_L$	Labor share	0.67
$\delta_K$	Fixed capital depreciation rate	0.02
$\delta_N$	Inventory depreciation rate	0.05
$\rho_a$	Persistence of aggregate productivity	0.98
$\sigma_a$	Conditional volatility of aggregate productivity	0.007
$\rho_z$	Persistence of firm productivity	0.911
$\sigma_z$	Conditional volatility of firm productivity	0.145
$\beta$	Time discount factor	0.997
$\gamma_0$	Constant price of risk parameter	3.22
$\omega$	Wage sensitivity to aggregate productivity	0.20

empirical results. Tables 9 and 10 present the parameters used in the calibration. We take the parameters of the firm-level productivity process from Imrohorglu and Tuzel (2011), which estimates firm production functions and generates firm-level productivity estimates using annual data. Importantly, the estimation that produces our firm-level productivity parameters includes industry fixed effects in productivity. In the interest of parsimony, we do not consider industry components in our model.

From Imrohorglu and Tuzel (2011), the persistence of the firm-level productivity process,  $\rho_z$ , is 0.911 ( $= 0.69^{1/4}$ ). The conditional volatility of firm productivity,  $\sigma_z$ , is computed from  $\rho_z$  and the cross-sectional standard deviation of (industry-adjusted) firm productivity as 0.145 ( $= 0.40 \times \sqrt{1 - 0.69^2} / \sqrt{4}$ ). The parameters of the production function,  $\alpha_C$  and  $\alpha_L$ , are in line with the estimates in real business cycle literature and roughly equal to the estimates in Imrohorglu and Tuzel (2011). We set  $\alpha_L = 0.67$  and  $\alpha_C = 0.3$ .<sup>10</sup>

We take the parameters of the aggregate productivity from King and Rebelo (1999). Their point estimates for  $\sigma_a$  and  $\rho_a$  are 0.979 and 0.0072, respectively, using quarterly data. The depreciation rate for fixed capital is set to 8% annually ( $\delta_K = 0.02$  quarterly), which is roughly the midpoint of values used in other studies. Cooley and Prescott (1995) use 1.6%, Boldrin, Christiano, and Fisher (2001) use 2.1%, and Kydland and Prescott (1982) use a 2.5% quarterly depreciation rate. In contrast, the depreciation rate of inventories is set at 20% ( $\delta_N = 0.05$  quarterly). This higher rate of depreciation is supported by a substantial

amount of industry research. Richardson (1995) argues that noninterest inventory carrying costs (which are equivalent to depreciation) range from 19% to 43% per year, and other trade publications report rates up to 35%.<sup>11</sup> We follow Bazdresch, Belo, and Lin, 2009 in choosing the wage function parameter  $\omega$  to equal 0.2, which matches the aggregate wage cyclicality estimated by Merz and Yashiv (2007).

We choose the pricing kernel parameters  $\beta$ ,  $\gamma_0$ , and  $\gamma_1$  to match the average annual riskless rate (1.14%), mean value-weighted excess stock returns (6.38%), and the Sharpe ratio (36.9%) measured from the data used in our empirical exercise. The parameter  $\beta$  establishes the constant riskless rate.  $\gamma_0$  sets the volatility of the pricing kernel, and therefore determines the level of the Sharpe ratio.  $\gamma_1$  determines the variation of the price of risk and has a primary role of matching the equity premium.<sup>12</sup> The adjustment cost parameters for fixed capital ( $\xi_K$ ) and inventories ( $\xi_N$ ) are picked to replicate the average firm-level volatilities of the investment to capital ratio (6.44%) and inventory growth (13.66%). These volatilities are estimated from annual firm data, divided by  $\sqrt{4}$  to transform into quarterly values, and then averaged across firms using value weights.<sup>13</sup>

We do not calibrate  $\nu$ , the parameter that determines the elasticity of substitution between fixed capital and inventory. Evidence on the value of  $\nu$  is scarce. Kydland and Prescott (1982) require it to be positive, so that the elasticity of substitution is less than one. They argue that “A priori reasoning indicates the substitution opportunities between capital and inventory are small, suggesting that  $\nu$  should be considerably larger than zero.” In their calibration,  $\nu$  takes the value of 4.0. The main model calibration in Christiano (1988) implies  $\nu = 3.6$ , which is in line with Kydland and Prescott’s (1982) result. On the other hand, many studies (e.g., Kydland, 1995) lump inventories together with fixed capital, implicitly assuming that the two are perfect substitutes, i.e.,  $\nu = -1$ . More recently, Gomes, Kogan, and Yogo (2009) have assumed a unit elasticity of substitution ( $\nu = 0$ ), while Belo and Lin (2012) use  $\nu = 0.5$ .

Rather than taking a firm stand on the value of  $\nu$ , we perform our calibration for several values of  $\nu$  between zero and 2.0. We present the midpoint of the range,  $\nu = 1$ , as our benchmark case. For each value of  $\nu$ ,  $s$  is picked to replicate the value-weighted average inventory/fixed capital ratio of 61% observed in firm-level data.

<sup>11</sup> The Annual State of Logistics Report from the Council of Supply Chain Management Professionals (2008) estimates costs of 19% annually, while Blackstone and Cox (2007) report rates from 10% to 35%. Lord (2008) claims that rates can run as high as 40% annually, but his figure is a total measure that includes the cost of capital.

<sup>12</sup> Greater time variation in the price of risk creates more “discount rate risk,” increasing the volatility of firm returns. With the Sharpe ratio effectively set by  $\gamma_0$ ,  $\gamma_1$  can be used to fit equity volatility and hence the equity premium.

<sup>13</sup> Since each observation is a sample moment computed using all observations for a given firm, the value weight is defined as the average weight of the firm in the market portfolio over that firm’s lifetime.

<sup>10</sup> We model technology as slightly decreasing returns to scale. It is well known that firm size is indeterminate with constant returns to scale technology. Since we do not clear the labor market, constant return to scale technology leads to explosive economies.

**Table 10**

Case-specific model parameters.

This table reports the values of parameters that vary across all calibrations. We consider three values of the parameter  $\nu$ , which determines the degree of complementarity between inventories and fixed capital. For each value of  $\nu$ , we choose  $\gamma_1$ ,  $\xi_K$ , and  $\xi_N$  to match moments estimated in the data. The parameter  $\gamma_1$ , which sets the degree of time variation in the volatility of the pricing kernel, is chosen to match the equity premium. The adjustment cost parameters for fixed capital,  $\xi_K$ , and inventories,  $\xi_N$ , are chosen to match the average firm-level volatilities of fixed capital and inventory investment. The table also reports one moment implied by the model, namely, the covariance between the firm's ratio of inventory to capital and its own productivity.

$\nu$	Complementarity	0	1*	2
$\gamma_1$	Time-varying price of risk parameter	-15.30	-14.75	-14.20
$\xi_K$	Adjustment cost parameter for fixed capital	27.50	29.70	29.90
$\xi_N$	Adjustment cost parameter for inventories	1.60	0.67	0.47
$\text{Cov}(\frac{N}{K}, z)$	Covariance between inventory to fixed capital ratio and firm-level productivity	9.88	8.52	7.38

\* Benchmark case.

### 3.4. Model results

Similar to Zhang (2005), the key mechanism relating investment to expected returns involves the interaction of convex adjustment costs and the countercyclical Sharpe ratio assumed in our pricing kernel. All risk derives from the firm's inability to freely adjust its capital following shocks to aggregate and firm-specific productivity. Since adjustment costs are lower for firms that are close to their optimal stock of capital, these firms have relatively low levels of risk. However, for firms that are well above or below their optimal capital levels, productivity shocks can have a much greater effect.

This risk is magnified when inventories and fixed capital become more complementary. When the two capital inputs are substitutes, firms optimally respond to shocks in productivity by mostly scaling their inventory inputs up and down. The main reason for this response is the lower adjustment costs associated with changing the stock of inventories. Hence, the firms' ratio of inventories to fixed capital becomes more volatile, and it moves more closely with firm-level productivity when the two inputs are substitutes. When the two inputs are complements, the ratio of inventories to fixed capital does not vary as much in response to productivity shocks. Higher complementarity therefore reduces the firm's flexibility in responding to shocks, as investment in one type of capital must be accompanied by a similar investment in the other.

Although firms at the highest and lowest extremes of investment in inventories and fixed capital will be riskiest, the countercyclical Sharpe ratio breaks the symmetry between these cases.<sup>14</sup> High rates of investment, while risky, tend to occur during expansionary periods when Sharpe ratios are low, while low rates of investment tend to occur during recessions when Sharpe ratios are high. The highest expected returns therefore tend to come from firms disinvesting during economic downturns. These

firms are the primary drivers of negative time series and cross-sectional relations between expected returns and inventory growth.

Out of the calibrated parameters,  $\beta$  and  $\gamma_0$  remain the same for all levels of the complementary parameter  $\nu$ .  $\gamma_1$ ,  $\xi_K$ , and  $\xi_N$  change with  $\nu$ , and their values are given in Table 10. The bigger changes in these parameters occur between  $\nu = 0$  and  $\nu = 1$ , whereas the parameters remain relatively flat between  $\nu = 1$  and  $\nu = 2$ .<sup>15</sup>

Confirming the intuition given above, higher complementarity tends to increase firm riskiness since the firm has less flexibility in responding to productivity shocks. Since we are calibrating the model to match the equity premium and volatility observed in the data, this higher level of risk is implied by the fact that the model needs a slightly lower  $\gamma_1$  to match these moments when  $\nu$  is high. Table 10 also shows that the covariance between the firm's own productivity and its ratio of inventory to fixed capital decreases in  $\nu$ . This supports the statement above that greater substitutability allows firms to respond to shocks mostly by changing the more easily adjusted level of inventories, while greater complementarity causes them to change both types of capital more evenly.

Table 11 presents results on the cross-section of returns. As in our empirical analysis in Section 2.6, we form quintile portfolios by sorting firms on the basis of past inventory growth. The table shows average expected returns and CAPM alphas of these portfolios as well as the spreads between the low and high portfolios. For each case, we present confidence intervals around the model-implied values of the spreads in returns and alphas. These are computed from one hundred simulations of 4,000 firms over 200 periods, which is roughly comparable to the length and average breadth of our empirical sample.

Table 11 shows that the relation between inventory growth and average returns or alphas is generally negative. Spreads in the average excess returns of low inventory growth and high inventory growth portfolios range from

<sup>14</sup> For simplicity, we assume symmetric adjustment costs, but asymmetric adjustment costs would also break this symmetry. Zhang (2005) and Tuzel (2010), for example, use asymmetric adjustment costs under which reducing the capital stock is more costly than increasing it. This asymmetry leads to differences in the risk levels of firms with low and high investment growth and will cause firms that are disinvesting to be more sensitive to productivity shocks. This mechanism would strengthen our results.

<sup>15</sup> The elasticity of substitution between fixed capital and inventories is  $1/(\nu+1)$ . The decline in elasticity is rather dramatic, from 1 to 1/2 as  $\nu$  moves from 0 to 1. As  $\nu$  goes up further, the change in elasticity is smaller, from 1/2 to 1/3 for  $\nu = 2$ .

For larger values of  $\nu$ , the production function becomes increasingly nonlinear. For  $\nu > 2$ , even high-order approximation methods lead to substantial solution errors. Hence, those cases are not reported.

**Table 11**

Model-implied excess returns and alphas of quintile portfolios formed on the basis of inventory growth.

This table reports model-implied mean excess returns and CAPM alphas for value-weighted quintile portfolios formed on the basis of past inventory growth. All values are based on one hundred simulations of 4,000 firms for two hundred periods (50 years). Point estimates are simulation averages, while confidence intervals (in parentheses) for the spreads in returns and alphas are constructed from the 5th and 95th percentiles of the simulated distributions of those spreads. All values are annualized and in percentage terms.

$\nu$	0	1*	2
Mean excess returns			
Low $\Delta \ln N$	7.55	8.23	9.04
2	7.65	7.25	6.73
3	7.18	6.63	6.07
4	6.40	5.99	5.61
High $\Delta \ln N$	4.34	4.70	5.30
Low–High	3.21 (2.19, 5.55)	3.53 (2.37, 6.35)	3.74 (3.74, 6.80)
CAPM alphas			
Low $\Delta \ln N$	0.54	0.84	1.09
2	0.78	0.51	0.23
3	0.51	0.18	–0.08
4	–0.02	–0.23	–0.36
High $\Delta \ln N$	–1.44	–1.14	–0.89
Low–High	1.98 (0.75, 2.92)	1.98 (0.32, 3.06)	1.99 (0.51, 3.05)

\* Benchmark case.

about 3.2% to 3.7% per year. Spreads in alphas are around 2% in all three cases. For excess returns, the spread increases with the complementarity parameter  $\nu$ . This confirms our intuition that greater complementarity reduces the flexibility of the firm since the more freely adjustable inventories cannot be as easily substituted for fixed capital. Although this reduced flexibility should have the largest effects on firms on both extremes—those with the highest and lowest levels of inventory growth—high inventory growth firms are more common in expansions, when Sharpe ratios are low. Low inventory growth firms are also risky, but they are most plentiful during recessions when the Sharpe ratio is high. This leads to the strong negative relation between inventory growth and excess returns.

While the spread in alphas is not as large as the spread in returns, it is nevertheless sizable. In short, the static CAPM does not explain average returns because CAPM betas vary over time in a way that is correlated with risk premiums. The low inventory growth portfolio, for example, has a high beta during recessions, when adjustment costs have the most bite for firms in that portfolio. During expansions, when firms in general are increasing inventories, firms in the low inventory portfolio may simply be staying put, implying low adjustment costs and relatively little risk.

We note that the low-minus-high spreads observed in the data, measured using unadjusted returns, are significantly larger than those generated in any of our calibrations. While the wide confidence interval for the excess return spread under the benchmark case includes the 5.73% value estimated in the data, the confidence interval

for the alpha spread does not include the empirical estimate of 6.23%.

However, for all  $\nu$ , the model-implied return spreads do match the industry-adjusted spreads from Table 7. This is perhaps a more appropriate target given the lack of industry effects in our model and the importance of industry effects in the data. Firms in our model are ex ante homogeneous, and our productivity parameters are from an estimation that includes industry fixed effects. On the other hand, Table 8 showed that the high and low inventory growth portfolios have a preponderance of firms from high-risk (more cyclical, more technology-intensive, longer lead times) industries, and a large fraction of the spread in returns and alphas appears to be industry-related. Our model therefore works about as well as one might expect given the absence of these features.

Table 12 contains comparative statics for most parameters of our model. To better isolate the effect of each parameter, we focus on small changes in the parameter values. Most of the results here are consistent with those from more standard models or with the intuition obtained from our calibrations under different values of  $\nu$ , so we review these results briefly.

As in the different calibrations, the comparative static results for  $\nu$  confirm that firm investment policy becomes more flexible as  $\nu$  decreases. For low  $\nu$ , inventory growth is more volatile than the benchmark case, while  $I/K$  is less volatile. This shows that firms respond to productivity shocks by changing the more easily adjustable level of inventories.

As a result of the flexibility that is gained as  $\nu$  decreases, the spread between the returns of low and high inventory growth firms decreases. The effect on the equity premium is slightly more complicated. The increase in flexibility reduces firm risk and should therefore decrease the average equity premium. However, an additional effect of lower  $\nu$  is to decrease the ratio of inventories to fixed capital (since the  $s$  parameter is fixed). Because fixed assets are riskier than inventories, this effect causes the average firm's risk to rise. Since the first effect dominates the second, at least for small changes in  $\nu$ , the equity premium declines as  $\nu$  decreases.

As is standard in models with convex adjustment costs, the adjustment cost parameters  $\zeta_K$  and  $\zeta_N$  primarily affect the volatility of investment, particularly the investment in fixed assets, for which adjustment costs are a bigger concern. Adjustment costs in fixed investment also affect the risk of fixed capital investment and hence the risk of the firm. Lower  $\zeta_K$  leads to lower risk and lower expected returns. Adjustment costs in inventories also affect firm risk, but since these costs are fairly low, their impact on risk and return is limited.

Faster depreciation of inventories, captured by the  $\delta_N$  parameter, leads to higher volatility in inventory growth and, due to complementarity, higher volatility in fixed investment as well. Higher depreciation leads to a higher equity premium and bigger spreads in inventory growth-sorted portfolio returns. Effectively, higher depreciation in inventories makes them more costly, causing firms to substitute into relatively risky fixed assets.

**Table 12**

Comparative statics.

This table contains comparative statics for our baseline specification with  $\nu = 1$ . The top row shows moments from the calibrated model, whose parameters are reported in Tables 9 and 10. The rows beneath show the moments that result from changing one parameter to the value given. Moments include  $E[R]$ , the market risk premium,  $SD(\Delta \ln N)$  and  $SD(I^K/K)$ , the average firm-level volatilities of inventory growth and fixed capital investment, and the mean excess returns on inventory-sorted portfolios. All results are obtained from one hundred simulations of 4,000 firms for two hundred periods (50 years). The two standard deviation columns show simulation means of value-weighted averages of firm-level standard deviations.

Case	$E[R]$	Avg. firm moments		Quintile portfolio mean excess returns						
		$SD(\Delta \ln N)$	$SD\left(\frac{I^K}{N}\right)$	Low $\Delta \ln N$	2	3	4	High $\Delta \ln N$	Low-High	
Benchmark	6.39	13.66	6.44	8.23	7.25	6.63	5.99	4.70	3.53	
Low $\nu$	$\nu = 0.9$	6.34	13.81	6.45	8.11	7.21	6.61	5.97	4.66	3.46
High $\nu$	$\nu = 1.1$	6.40	13.54	6.52	8.32	7.26	6.62	5.98	4.71	3.62
Low $\xi_K$	$\xi_K = 29.6$	6.38	13.68	6.47	8.22	7.24	6.63	5.99	4.69	3.54
High $\xi_K$	$\xi_K = 29.8$	6.41	13.64	6.41	8.26	7.27	6.66	6.02	4.73	3.53
Low $\xi_N$	$\xi_N = 0.65$	6.38	13.76	6.46	8.23	7.23	6.62	5.98	4.70	3.54
High $\xi_N$	$\xi_N = 0.69$	6.39	13.52	6.43	8.22	7.26	6.65	6.00	4.68	3.53
Low $\delta_N$	$\delta_N = 0.045$	6.17	13.17	6.38	7.90	7.02	6.44	5.81	4.52	3.38
High $\delta_N$	$\delta_N = 0.055$	6.54	14.16	6.55	8.51	7.42	6.77	6.11	4.82	3.69
Low $\gamma_0$	$\gamma_0 = 3.20$	6.30	13.60	6.34	8.06	7.12	6.53	5.91	4.68	3.38
High $\gamma_0$	$\gamma_0 = 3.24$	6.46	13.73	6.55	8.39	7.36	6.72	6.06	4.69	3.69
Low $\gamma_1$	$\gamma_1 = -14.5$	6.26	13.63	6.41	8.05	7.10	6.50	5.87	4.61	3.43
High $\gamma_1$	$\gamma_1 = -15$	6.54	13.69	6.47	8.45	7.43	6.79	6.14	4.81	3.64
Low $\omega$	$w = 0.1$	6.54	13.70	6.49	8.38	7.39	6.78	6.14	4.85	3.53
High $\omega$	$w = 0.3$	6.24	13.62	6.39	8.09	7.11	6.50	5.85	4.58	3.51

**Table 13**

Model-implied regression coefficients.

This table reports regression results based on model data simulated under our benchmark calibration. All values are based on one hundred simulations of 4,000 firms for two hundred periods (50 years). Point estimates are simulation averages, while confidence intervals (in parentheses) are constructed from the 5th and 95th percentiles of the simulated distribution of each coefficient. As in the empirical section, aggregate regressions are based on aggregate inventories ( $N$ ) and sales ( $Y$ ), expected future sales growth, and the market risk premium. Expected sales growth and the risk premium are computed within the model, and the regression method is standard OLS. Firm-level regressions are pooled across firms and time. Variables in the firm-level regression are similar except that inventories, sales, and risk premiums are firm-specific, and lagged sales growth is used in place of expected future sales growth. All expectations are conditional on time  $t-1$  information.

Aggregate			
$\Delta \ln N_t = b_0 + b_1 \ln\left(\frac{N_{t-1}}{Y_{t-1}}\right) + b_2 E[\Delta \ln Y_t] + b_3 E[R_t] + \epsilon_t$			
$b_0$	$b_1$	$b_2$	$b_3$
0.51	-0.13	0.48	-0.82
(-0.15, 1.54)	(-0.23, -0.05)	(0.23, 0.68)	(-1.56, -0.35)
Firm-level			
$\Delta \ln N_{i,t} = b_0 + b_1 \ln\left(\frac{N_{i,t-1}}{Y_{i,t-1}}\right) + b_2 \Delta \ln Y_{i,t-1} + b_3 E[R_{i,t}] + \epsilon_{i,t}$			
$b_0$	$b_1$	$b_2$	$b_3$
0.80	-0.01	0.18	-0.69
(0.33, 1.29)	(-0.01, -0.01)	(0.17, 0.19)	(-1.20, -0.22)

Changing the pricing kernel parameters  $\gamma_0$  and  $\gamma_1$  yields predictable results. While the two parameters play different roles, an increase in the absolute value of either parameter will raise the equity premium, and return spreads rise in an approximately proportional manner. As the result of greater variation in expected returns, both types of investment become more volatile as well.

Finally, lowering the sensitivity of wages to aggregate productivity ( $\omega$ ) increases both risk and the risk premium. This is due to the fact that wages do not fall as far

in recessions or rise as much in expansions, causing firms to make more extreme adjustments to the quantity of labor and leading to larger fluctuations in output. This effect also causes higher volatilities in inventory and fixed investment.

Table 13 contains the final set of model results. Using the same simulation design as in Table 11, we compute model-implied regression coefficients corresponding to the aggregate- and firm-level regressions estimated in the empirical section. We report results only for the

benchmark calibration, as other calibrations generate similar results.

In general, the model-implied coefficients are similar to those estimated in the data, and all coefficients have the correct signs. Most importantly, the model implies a significant negative coefficient on the cost of capital, both at the aggregate and firm levels. At the aggregate level, the model-implied coefficient of  $-0.82$  is larger than those observed in the data, though in unreported long-horizon regressions using durable industries, we obtain coefficients that are comparable. At the firm level, the model-implied coefficient of  $-0.69$  is within the range of estimates we obtain from different specifications and data sources. The coefficients on expected or lagged sales growth are in line with those estimated from the data, while the coefficient on the lagged ratio of inventories to sales is too large in the aggregate regression and too small in the firm-level regression.

#### 4. Conclusion

Our results demonstrate that inventory investment is affected by time series and cross-sectional variation in the cost of capital. Unlike earlier work that focuses only on variation in the real interest rate, we identify fluctuating risk premiums as a significant driver of inventory growth at the aggregate, industry, and firm levels. As in most of the prior literature, we find no relation between real interest rates and inventory growth.

The relation between risk premiums and inventory investment is stronger in riskier industries, namely, those that produce durables rather than nondurables, exhibit greater cyclicality in sales, require longer lead times in production, and are subject to more technological innovation. We confirm earlier results that spreads in returns and alphas across portfolios formed on the basis of past inventory growth are large, but we find that close to half of each spread is an industry rather than firm effect. Furthermore, firms in the extreme quintiles are systematically different from those in quintiles 2–4, as they tend to come from industries that measure higher in terms of our four risk proxies.

We develop a theoretical model of firm production with two types of capital, fixed capital and inventories, and investigate its performance in matching the relationships between inventory investment and risk premiums that we observe in the data. Our results show that these relationships will be stronger when fixed capital and inventories are more complementary. The ability to substitute between the two types of capital gives firms additional flexibility due to the fact that inventories are more easily adjusted. When fixed capital and inventories are more complementary, firms lose this flexibility, making adjustment costs on fixed capital more binding for unproductive firms and increasing the spread between high and low inventory growth firms.

In sum, we find that most of our empirical results are captured by the model reasonably well. The model generates cross-sectional and time series relations between risk premiums and inventory growth that are similar to those observed in the data, particularly when we impose a

higher level of complementarity between inventories and fixed capital. While the model fails to match the full spread in the returns or alphas of low and high inventory growth firms, our empirical work shows that much of this spread is driven by firms from industries that are significantly riskier than average. These results suggest that industry-level heterogeneity is an important feature of the data and that adding industry effects may be a useful extension for future work.

#### Appendix A

For deflating our aggregate nominal inventories and shipments data, we either use the PPI for manufactured goods, durable manufactured goods, or nondurable manufactured goods depending on the type of good. For industries, we use the PPI series suggested by Roberts, Stockton, and Struckmeyer (1994). In several cases, when PPI data are only available for subsectors of a given industry, we follow their approach and aggregate the subsector-level series into an industry-level series by taking shipments-based weighted averages. In all cases, PPI data are not seasonally adjusted, so we seasonally adjust them using the U.S. Census' X12a program.

In the M3 database, most data series are available monthly from January 1958 until the end of our sample in December 2010. Prior to 1992, industry classifications are based on the Standard Industrial Classification (SIC) codes. Between January 1992 and March 2001, both SIC and NAICS (North American Industry Classification) codes are used, but after March 2001 the database includes only NAICS codes. Data for broad categories such as manufacturing, durables, and nondurables are labeled the same way both based on SIC and NAICS codes. For industry-level data, we match SIC and NAICS codes using the "Dispersement of M3 SIC Categories" and "Origination of M3 NAICS Categories" files from the M3 Web site. We consider SIC- and NAICS-based industries "matched" if more than 90% of the SIC industry is dispersed into a given NAICS industry for which data are available and more than 90% of the NAICS industry originates with that same SIC industry. In some cases, one SIC industry is dispersed into multiple NAICS industries in such a way that the NAICS industries combined meet our criteria for inclusion, which we then splice onto the single SIC industry.

Though the levels of inventory and shipments data differ between SIC-based and NAICS-based industries, their growth rates are quite similar over the 1992–2001 period when both classifications were used. We therefore use data reported based on SIC codes until March 2001 and then extend the series by splicing NAICS-based growth rates starting in April 2001.

An additional adjustment is necessary due to the fact that the M3 database switched its inventory accounting method beginning in 1982. Prior to that year, inventory figures were book value estimates. Current costs were used starting in 1982, resulting in a jump in the value of recorded inventories. We eliminate this accounting artifact by assuming zero inventory growth from December

**Table A1**

Corresponding M3 and PPI series.

This table describes how we like SIC and NAICS industries. The industry name is from the SIC system. The SIC column contains the code used in the M3 database to denote that SIC-based industry. NAICS is the code used in the M3 database to describe a NAICS-based industry. Deflator code and PPI Series are the code and name, respectively, used by the Bureau of Labor Statistics to describe the PPI series that we use to deflate the corresponding shipments and inventories data.

Industry name	SIC	NAICS	Deflator code	PPI Series
Stone, clay, and glass	32 M	27S	wpu13	Nonmetallic mineral products
Primary metals	33 M	31S	wpu101	Iron and steel
			wpu1022	Primary nonferrous metals
Fabricated metals	34 M	32S	wpu107	Fabricated structural metal products
			wpu108	Miscellaneous metal products
Industrial machinery	35 M	33S	wpu11	Machinery and equipment
			wpu117	Electrical machinery and equipment
Electronic equipment	36 M	34S+35S	wpu117	Electrical machinery and equipment
			wpu124	Household appliances
			wpu125	Home electronic equipment
Transportation equipment	37 M	36S	wpu141	Motor vehicles and equipment
Food	20 M	11S+12A	wpusop2110	Food manufacturing
Tobacco	21 M	12B	wpu152	Tobacco products
Paper	26 M	22S	wpu0913	Paper
Chemicals	28 M	25S	wpu061	Industrial chemicals
Petroleum products	29 M	24S	wpu057	Petroleum products, refined
Rubber	30 M	26S	wpu07	Rubber and plastic products
All manufacturing			wpudur0200	Manufactured goods
All durable manufacturing			wpudur0211	Durable manufactured goods
All nondurable manufacturing			wpudur0222	Nondurable manufactured goods

1981 to January 1982 and rescaling post-1982 data accordingly.

Table A1 summarizes the data series used. Industry name is from the SIC classifications. SIC denotes the code used in the M3 database to denote that SIC-based industry. NAICS is the code used in the M3 database to describe a NAICS-based industry. Deflator code and PPI Series are the code and name, respectively, used by the Bureau of Labor Statistics to describe the PPI series that we use to deflate the corresponding shipments and inventories data.

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