New Orders and Asset Prices

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We investigate the asset pricing and macroeconomic implications of the ratio of new orders (NO) to shipments (S) of durable goods. NO/S measures investment commitments by firms, and high values of NO/S are associated with a business cycle peak. We find that NO/S proxies for a short-horizon component of risk premia not identified in prior work. Higher levels of NO/S forecast lower excess returns on equities and many types of bonds, at horizons from one month to one year. These effects are generally robust to the inclusion of common return predictors and are significant on an out-of-sample basis as well. We also address the term structure of risk premia by constructing a similar ratio to measure longer-term investment commitments, which predicts returns primarily at longer horizons. (*JEL* G12, E32, E44)

Durable goods spending represents physical capital investment by businesses and households. As such, standard theory predicts that the decision to undertake these investments will be based on the discounted value of the future profits or service flows provided by the durable good. As long as some of the variation in these discounted values is due to time variation in risk premia, the amount of durable purchases should forecast future excess security returns with a negative sign.

Cochrane's (1991) seminal paper showed that the relation between the aggregate investment/capital ratio and future stock market returns was indeed negative. The effect, however, is somewhat weak, and Baker and Wurgler (2000), using a different timing convention and investment definition, find no link at all.

Notwithstanding the weakness of the evidence, its interpretation is also unclear. In Cochrane's (1991) view, investment's ability to forecast future market returns reflects rational responses to variation in aggregate risk

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premia. Other authors undermine this interpretation, however, arguing that equity mispricing is an important determinant of corporate investment.[1] The mispricing explanation also predicts that high levels of investment should be associated with low future returns.

In this paper, we introduce a new measure of investment commitments based on new orders of durable goods and show that it has strong predictive ability for future returns on stocks and bonds, both in- and out-of-sample. The patterns in this predictability are generally consistent with an explanation based on rational risk premia rather than one based on mispricing. In addition, our measure has strong predictive power for a number of macroeconomic variables.

As discussed by Cochrane (1991), Lamont (2000), Kuehn (2008, 2010), and others, investment lags may obscure the relationship between investment and the cost of capital. We focus on new orders because they measure investment at the time that the purchase decision is made (formally, when they become "supported by binding legal documents") rather than the time that the goods are delivered or installed. Our series should therefore measure investment precisely at the time the firm commits to making it.

The growth of new durable orders is commonly used as an indicator of future manufacturing output and of macroeconomic activity in general, a practice whose value is confirmed in our results. Our primary focus, however, is on the ratio of new orders (NO) to shipments (S) of durable goods. Since new orders represent commitments to future investment while shipments can be interpreted as current investment, the ratio of the two (NO/S) should provide a measure of future investment growth.

Both new orders and shipments series are available on a monthly basis from the Census Bureau, and both are available for all durable goods in aggregate and for various subsets of these goods, such as consumer durables or capital goods. This permits us to examine whether industry-level behavior differs from the aggregate, and also to focus on more traditional definitions of investment (e.g., capital goods excluding defense and aircraft) in addition to the broad measure we examine primarily.

Our analysis has three main goals. The first is to characterize the relationship between NO/S, the ratio of new orders to shipments, and the state of the macroeconomy. Our results suggest that NO/S is a type of "peak indicator," taking its highest values just prior to peaks in output, consumption, employment, and investment. We find a particular tendency of high NO/S to follow periods of prolonged growth in consumption and that it is significantly related to a measure of surplus consumption constructed under the Campbell and Cochrane (1999) model.

[1] Examples include Chirinko and Schaller (2001), who examine aggregate investment in Japan, and Baker, Stein, and Wurgler (2003), who focus on U.S. firms.

Our second goal is to test whether NO/S has predictive power for future asset returns and output growth rates. We find that higher NO/S is associated with lower stock returns, a result that mirrors those of Cochrane (1991) and Lamont (2000). These results are robust to the inclusion of a number of control variables, such as Lettau and Ludvigson's (2001) *cay* and the output gap measure of Cooper and Priestley (2009). We also find that NO/S forecasts the returns on a wide cross-section of bonds, specifically those of long- and intermediate-term Treasury bonds and high- and low-grade corporate bonds. This predictability is not just apparent in-sample, but out-of-sample as well. Furthermore, we show that NO/S is a useful predictor of future output growth, even after controlling for other known predictors, though short-horizon and long-horizon forecasts depend on NO/S with opposite signs. This is in contrast to variables like the dividend yield that appear to predict returns but not growth.[2]

Our third goal is to differentiate between rational and behavioral explanations. The finding that high NO/S follows periods of rising consumption and forecasts low future returns suggests a rational risk-premia explanation. One prominent model that might generate this behavior is that of Campbell and Cochrane (2001), in which a high consumption surplus decreases risk aversion, leading to lower risk premia. Although the model is silent about investment behavior, the decrease in risk premia would plausibly imply an increase in investment in a general equilibrium setting with production.

However, there are at least two alternative explanations of these basic findings. One that has been put forth in the behavioral corporate finance literature is that the predictability is driven by mispricing, with managers responding to overpriced equity by increasing investment. Some of our results suggest another possibility, not necessarily in conflict with the previous one, in which the high NO/S observed following periods of strong economic growth is the result of businesses "overshooting" by investing too heavily under the assumption that past trends will continue and corporate profits will be high. As subsequent growth realizations reveal the degree of overoptimism, both investment and stock prices fall. While this explanation does not seem to have been offered before, the idea of excessive extrapolation is not new. Bernartzi (2001), for example, finds strong evidence of this type of behavioral bias in employee allocations to 401(k) plans.

While we cannot completely rule out a behavioral explanation consistent with our empirical evidence, we provide several results that go against the overshooting hypothesis. One is that NO/S forecasts the returns on Treasury bonds, in addition to stocks, which should be immune to misvaluation arising

[2] The significance of the dividend yield as a predictor of stock returns has been challenged in several recent papers. Ang and Bekaert (2007) claim that its significance as a long-horizon return predictor is overstated. Goyal and Welch (2008) argue that it, like most other predictive variables popular in the literature, suffers from poor out-of-sample performance, particularly over the last 30 years.

from biased cash flow forecasts. Next, we assess the relative importance of aggregate versus industry-level NO/S in forecasting industry returns. If the predictability of returns is the result of overshooting, then we would expect this predictability to be stronger at the industry level. This would imply that an industry's own NO/S should have a particular ability to forecast that industry's returns. Instead, we find that industry-level NO/S offers no additional explanatory power. Third, we examine the prices of investment goods. If there is overshooting in the demand for investment goods, then the resulting oversupply should result in declining prices. Instead, we find that high NO/S actually forecasts rising investment goods prices.

We also examine the "term structure" of risk premia. We construct a series similar to NO/S based on construction starts and completions. Tuzel (2010) argues that the greater durability of structures relative to capital equipment makes them more risky. An implication that she does not pursue is that greater durability also implies that the correct discount rate to apply to structures investment is a longer "maturity" rate. In contrast, the durable goods on which NO/S is based are primarily capital goods as well as intermediate goods used in manufacturing and other industries, all of which represent shorter-term investments. For that reason, the discount rate reflected in NO/S is likely to be from the shorter end of the term structure. Therefore, if time-varying risk premia is the main driver of return predictability, orders of durable goods should forecast future returns at short horizons, while construction starts should forecast returns at long horizons. In contrast, if durables and starts are driven by systematic forecast errors, then the horizon over which returns are predictable by each measure should be determined by the time it takes for the forecast errors to be recognized. It is not obvious why this would be related to the durability of the investment type.

In regressions that use both NO/S and the ratio of construction starts to completions, we find patterns in predictability that are consistent with the risk premia hypothesis. While NO/S has some predictive power at long horizons, its predictive power generally decreases at horizons longer than one year. In contrast, the predictive ability of the starts to completions is weakest at short horizons, but it steadily increases and is highly significant at horizons of several years or longer.

Our findings add to the literature on asset return predictability in several ways. From its inception in papers such as Fama and Schwert (1977) and Keim and Stambaugh (1986), the return predictability literature has focused almost exclusively on price-based predictors, variables like the dividend yield or the term spread that are constructed entirely or in part from security prices. The fact that these endogenous predictors are generally highly persistent raises the possibility, articulated most clearly by Stambaugh (1999), that much of the evidence favoring predictability suffers from potentially severe statistical biases. Another critique of that literature is the poor out-of-sample performance of most predictive models, with Goyal and Welch (2008) arguing that such models would generally not have helped an investor outperform the market.

NO/S differs from most common predictors because it is not constructed using any price data and because it is not persistent, having a quarterly autocorrelation of just 0.57, as compared with 0.97 for the dividend yield. According to Stambaugh (1999), the bias in our predictive regressions should be close to zero. Furthermore, our predictive regressions perform relatively well on an out-of-sample basis, with out-of-sample R-squares that often approach the respective in-sample values.

Our results suggest that NO/S captures a short-term component of expected returns that is not spanned by existing predictive variables. This is a natural consequence of the low autocorrelation of NO/S, and it is evident from our finding that NO/S forecasts returns most strongly at relatively short horizons, with R-squares usually peaking at horizons between one month and one year. The existence of risk premia components with different frequencies has also been documented by Lochstoer (2006), who finds evidence of components with business cycle and "generational" frequencies, but NO/S appears to operate at a frequency much higher than those identified by Lochstoer.

Our results also link these components of return predictability and the real economy. While much of the return literature focuses on predictors that are at least somewhat mechanically related to expected returns given their dependence on market prices, our predictors capture variations in the cost of capital that are reflected in real investment decisions. Not only does our analysis of these predictors confirm Cochrane's (1991) apparently fragile finding of a link between aggregate investment and future returns, but it also shows that the link is different in the short-term and long-term in exactly the way one would predict based on standard theory.

Our paper shares a number of similarities with Lamont (2000), who examines a survey-based measure of planned investment growth. However, our findings go significantly beyond those reported by Lamont. Specifically, our analysis shows that NO/S is related to other macroeconomic variables in a way that suggests it proxies for risk premia, that it forecasts future bond returns, and that it forecasts stocks and bonds on an out-of-sample basis. More importantly, we present a number of tests designed to distinguish between a rational risk premia-based explanation and several alternatives based on behavioral biases.[3] In addition, our analysis avoids the look-ahead bias that affects many of Lamont's results. That bias stems from the fact that he forecasts calendar-year investment

[3] In an attempt to rule out a behavioral explanation, Lamont runs a regression in which he regresses future stock returns on the equity share of Baker and Wurgler (2000) in addition to his own investment plans series. The premise is that the equity share proxies for equity mispricing, which implies that the significant incremental effect of investment plans must therefore be capturing risk premia. This approach is crucially dependent on the equity share representing a pure measure of mispricing and not reflecting rational variation in equity issuance, as Pastor and Veronesi (2005) suggest.

and returns using an investment plans series that is often not collected until February or March of the same year.

In the next section, we introduce our data and describe the properties of NO/S. Results describing how NO/S is related to business cycle variables are in Section 2. Section 3 discusses the link with existing theoretical models, while return predictability results appear in Section 4. We conclude in Section 5.

1. Data

The central focus of this paper is on the ratio of new orders (NO) of durable goods to shipments (S) of durable goods. Used most often in the electronics industry, this "book-to-bill ratio" is commonly viewed as a predictor of future growth. *The Wall Street Journal* describes the ratio as "the amount of new orders versus the amount of actual products shipped. A ratio higher than one means new orders outpaced shipments, implying a good business outlook."[4] Since all durable goods can be interpreted as some type of capital investment, either by corporations or by households, the ratio of new orders to shipments of durable goods is a natural measure of future investment growth.[5] If new orders rise, future investment must therefore rise at some horizon as long as there is not an increase in canceled orders or a permanent rise in unfilled orders.

Both new orders and shipments data are from the Census Bureau's Survey of Manufacturers' Shipments, Inventories, and Orders, also known as the M3 Survey. This is a monthly survey of firms representing about 60% of the total value of U.S. manufacturing output. Most manufacturing firms with more than $500 million in annual sales are represented, and a number of smaller firms are included as well. The results for a given month are released near the end of the following month, making the survey one of the most current measures of economic activity. Although we mainly use the data on total durable goods, the survey includes series disaggregated by goods type and industry. We consider these briefly in Section 4.

We use several series from this survey, the most important of which are new orders of durable goods (NO) and the value of shipments of durable goods (S). Reported values for new orders are net of cancellations, which means that shipments and new orders obey the identity

$$NO_{t+1} = S_{t+1} + UO_{t+1} - UO_t,$$

where UO denotes unfilled orders. Thus, the ratio of new orders to shipments can also be described as a measure of the change in unfilled orders. This relates NO/S to another common proxy for company or industry health, namely the order backlog.

[4] "Orders for Japanese Chip Equipment Rise 44%," *The Wall Street Journal*, June 20, 2006.

[5] As argued by Eberly (2002), consumer durable expenditures can be considered a form of capital investment by households.

All M3 series are available in seasonally adjusted form, and we use these versions. All data from the survey are nominal, though since our primary focus is on the ratio of new orders to shipments a price deflator is often unnecessary. In a few places we will examine new orders and shipments separately. When we do so, we deflate these values using the PPI for durable manufactured goods. PPI data are not seasonally adjusted, so we seasonally adjust them using the U.S. Census's X12a program. We also make use of price deflators for private domestic fixed investment, equipment investment, and GDP from NIPA Table 1.1.3.

In the M3 database, data on durable goods are available monthly from February 1958 to the end of our sample in December 2009. Prior to 1992, industry classifications (used to determine whether an industry is a durable or non-durable goods producer) are based on Standard Industrial Classification (SIC) codes. Between January 1992 and March 2001, both SIC and NAICS (North American Industry Classification) classifications are used, but after March 2001 the database includes only the NAICS series. A complication that arises when using NAICS data is that the semiconductor industry is represented in shipments but not in new orders, causing the ratio of new orders to shipments to be artificially low. In order to make our shipments series compatible with new orders, we subtract out the shipments of semiconductors. While a preferable remedy would be to add new orders of semiconductors to the durable new orders series, those data are not collected.

When we compute ratios of new orders to shipments using the two classification systems, the ratios coincide almost exactly at the beginning of 1992. We therefore construct our NO/S series simply by using the SIC-based NO/S ratio up to February 1992 and the NAICS-based ratio (with the semiconductor adjustment) from March 1993 on. In the few places where we analyze new orders and shipments separately, we extend the earlier SIC-based series by splicing on the NAICS-based growth rates starting in March 1992.

The logarithm of the NO/S ratio is plotted in the top panel of Figure 1, and summary statistics are reported in Table 1. The shaded regions in the figure denote NBER recessions, and visual inspection suggests that NO/S tends to rise gradually during expansionary periods and fall dramatically during contractions. In particular, we see that the biggest changes in NO/S, namely the drops in 1974–1975 and 2007–2008, were large downward moves that occurred in the midst of a recession. It is also apparent that the NO/S series is not very persistent relative to other return predictors like the earnings yield or *cay*. The one-month autocorrelation is just 0.66, and the one-year autocorrelation is 0.14. Using both the augmented Dickey-Fuller (Said and Dickey 1984) test and the Perron and Phillips (1988) test, we can reject a unit root in NO/S at all conventional significance levels. These findings should, to a large extent, ease concerns about the bias in predictive regressions discussed by Stambaugh (1999) and the spurious regression bias studied by Ferson, Sarkissian, and Simin (2003).

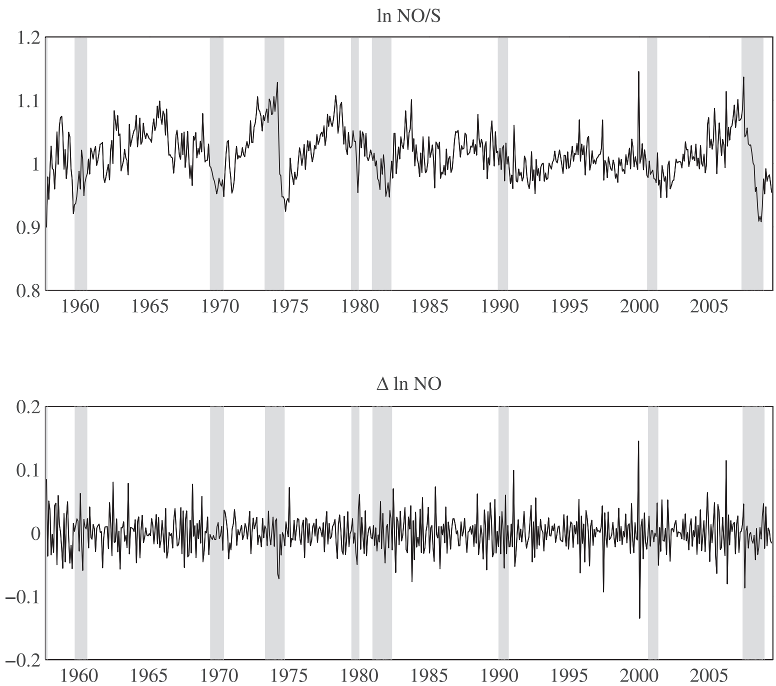

Figure 1
The ratio of new orders to shipments and new orders growth
The top panel of this figure plots the logarithm of the ratio of new orders of durable goods to shipments of durable goods. The bottom panel plots growth rates of the new orders series. Shaded areas denote NBER recessions. Data are monthly from 2/1958 to 12/2009.

Table 1
NO/S summary statistics

	Levels:	First differences		
	ln NO/S	ln NO/S	ln NO	ln S
Full sample mean	0.0142	0.0001	0.0020	0.0019
NBER expansion mean	0.0172	0.0004	0.0049	0.0045
NBER recession mean	−0.0029	−0.0015	−0.0140	−0.0126
t-statistic of difference	−1.9576	−0.5706	−5.4855	−7.9923
Full sample standard deviation	0.0363	0.0287	0.0351	0.0210
NBER expansion standard deviation	0.0330	0.0286	0.0340	0.0204
NBER recession standard deviation	0.0476	0.0296	0.0370	0.0189
t-statistic of difference	1.3022	0.3002	1.8384	0.8219
1st order autocorrelation	0.6913	−0.3789	−0.2524	−0.1169
12th order autocorrelation	0.1279	−0.0386	−0.0072	−0.0979
Augmented Dickey-Fuller statistic	−14.0142	−36.2476	−31.7125	−28.7753
Phillips-Perron statistic	−30.5201	−29.7864	−32.1905	−35.0484
Correlation with excess stock returns	−0.0521	0.0118	0.0538	0.0892

This table reports summary statistics on new orders of durable goods, shipments of durable goods, and their ratio. Data are monthly from 2/1958 to 12/2009. Augmented Dickey-Fuller and Phillips-Perron statistics correspond to tests of the null hypothesis that the series has a unit root. Both tests are implemented with 12 lags, and both have a 1% critical value of −3.46.

For comparison, the bottom panel of Figure 1 plots the growth rate of new orders, a series that is frequently cited in the press as an indicator of the business cycle trend. Table 1 shows that this series is significantly higher in expansions than in recessions, but it is strikingly noisy with no measurable persistence. Most likely because of this high level of noise we find that this variable has little predictive ability beyond a horizon of just a few months.

Several other statistics presented in Table 1 are also notable. First, growth rates in both new orders and shipments decline in recessions and rise in expansions, as would be expected. However, despite some visual evidence that suggests a procyclical ratio of new orders to shipments, we find no significant differences between expansions and recessions, either in levels or growth rates.[6] Second, growth in new orders is substantially more volatile than growth in shipments, indicating that new orders may respond faster to changes in business conditions than do actual shipments. Third, none of the four series being analyzed is very correlated with the excess returns on the stock market. This also contrasts strongly with the dividend yield and *cay*, whose first differences have correlations with the market return of roughly −0.9 and −0.5, respectively.

Our variable is related to the planned investment growth series examined by Lamont (2000). The use of that series was motivated by Cochrane's (1991) argument that lags in the investment process may obscure relations between risk premia and investment, but not with investment plans. The annual series used by Lamont was based on a survey conducted once per year from 1948 to 1994 by the Commerce Department in which firms were asked for their planned level of capital expenditures over the next year. Lamont constructs a planned investment growth series by dividing the investment plans data by the actual level of capital expenditures in the previous year. He finds that planned investment growth predicts both actual investment and excess stock returns.

With a correlation coefficient of 0.29, the ratio of new orders to shipments is only moderately correlated with Lamont's planned investment growth data.[7] It is unclear whether the dissimilarity of these series arises from differences in timing or smoothing, the fact that new orders and shipments include consumer durables in addition to investments by businesses, or other unknown factors.[8] Our series also differs substantially in that it is monthly and remains currently available.

6 In this section and in Sections 2 and 3, all standard errors are computed using the method of Newey and West (1987), with the number of lags guided by the Newey and West (1994) approach.

7 We compute this correlation using February values of NO/S since this is the month in which the investment plans survey was usually collected.

8 Whatever the reason, NO/S turns out to be a better predictor of future stock and bond returns. Lamont's series, which he assumes is available in February, forecasts the subsequent March returns very well. However, it has no significant predictive ability for stock or bond returns for the remainder of the year, at least during the 1958–1994 sample period. This is problematic given that Lamont notes in his first footnote that the survey was not actually taken until March for a large part of his sample, meaning that the investment plans series may suffer from a look-ahead bias.

As a counterpart to new orders from the nonresidential construction sector, we use the new nonresidential building starts data collected by McGraw-Hill Construction (Dodge). Announcements by Dodge, which are typically made toward the end of the following month, are usually covered by newspapers such as *The Wall Street Journal* and trade publications such as *Pit & Quarry*. We hand-collected the data from past issues of these publications starting in January 1958. We scale the new building starts data with the total value of private and government nonresidential structures investment from NIPA Table 5.2.5. Since the building starts data are only available in seasonally unadjusted form prior to 1985, we seasonally adjust them, again using the X12a program. Structures investment is available only at the annual frequency.[9]

To compute the ratio of building starts to structures investment (Starts/SI), we divide each month's construction starts with the most recent annual value of structures investment. The resulting series is different from NO/S in several respects. First, ln Starts/SI is significantly more volatile, with a standard deviation of 0.166, as opposed to 0.036 for ln NO/S. More importantly, it is much more persistent, with monthly and annual autocorrelations of 0.83 and 0.60, respectively, as opposed to 0.66 and 0.14 for ln NO/S.

We augment these series with standard data items. Quarterly dividends and corporate earnings are from Robert Shiller's Web site, and per capita consumption and *cay* are from Martin Lettau's Web site. Quarterly GDP, investment, and inventory series are from BEA NIPA tables, and monthly industrial production is from the Federal Reserve Board. The civilian unemployment rate is from the Bureau of Labor Statistics. The output gap measure of Cooper and Priestley (2009) is computed as the residual in the regression of industrial production on a time trend and a squared time trend.

Market returns, industry returns (38 industries), and riskless rates are from Kenneth French's Web site. Long-term Treasury, intermediate-term Treasury, and investment-grade corporate bond returns are from Ibbotson. For high-yield corporate bonds, Ibbotson returns are used through May 2005, after which they are not available. The corresponding Lehman/Barclays total return index is used after that.

Long-term Treasury, long-term corporate (Baa), and short-term (three-month) Treasury yields are from the Federal Reserve Board's H15 survey. The term spread is computed as the difference between long-term and short-term Treasury yields, and the default spread is the difference between long-term corporate and Treasury bond yields. The dividend yield is defined as the four-quarter sum of S&P Composite dividends divided by the current index level. The Cochrane and Piazzesi (2005) "tent" factor is computed using the parameter values reported in their paper and the Fama-Bliss discount bond yields from

9 Private nonresidential structures investment is available at the quarterly frequency, but government investment is annual only. Since construction starts data include both private and government components, we include both in the denominator as well.

CRSP. The investment-capital ratio examined by Cochrane (1991) is from Amit Goyal's Web site.

2. Relationships between NO/S and Economic Activity

In this section, we examine the relationship of NO/S with past and future trends in economic aggregates. Our primary goal is to understand the role of NO/S in the business cycle and to assess whether NO/S is useful in predicting future changes in measures of economic activity.

2.1 Placing NO/S within the business cycle

We begin our empirical analysis by characterizing the conditions under which NO/S tends to be high or low. We first examine how new orders and shipments affect and are affected by their ratio, NO/S, with the goal of understanding, initially at a somewhat mechanical level, the determinants of NO/S.

Table 2 contains the output from a number of regressions in which the dependent variable is the log ratio of new orders to shipments. The first three regressions relate NO/S to past four-quarter growth rates in new orders and shipments. We compute *t*-statistics, which are shown in parentheses, using Newey and West (1987) standard errors. Not surprisingly, NO/S tends to be high following positive growth in new orders, particularly over the last year. Less predictable is that NO/S also tends to be high following positive growth in shipments. When both variables are included, only the growth in new orders is significant. Thus, high levels of NO/S do not generally arise from falling shipments, but from new orders that are rising more quickly than shipments.

The subsequent mean reversion toward more typical values of NO/S occurs in much the same way. When NO/S is high, future shipments are generally falling, not rising, but since new orders are falling even faster the ratio as a whole tends to decrease. This can be seen in Figure 2, which provides a graphical depiction of predictability in new orders and shipments. Non-overlapping one-month growth rates are regressed on lagged ln NO/S, i.e.,

$$\ln Y_{t+\tau} - \ln Y_{t+\tau-1} = \alpha + \beta \ln NO/S_t + \epsilon_t, \tag{1}$$

where Y denotes either new orders or shipments. The figure displays the resulting slope coefficients and their 95% confidence intervals as a function of the forecast horizon τ.

In Figure 2, we see that following a high level of NO/S, new orders initially fall and shipments initially rise, both effects causing a decline in NO/S. The rise in shipments is short-lived, however, lasting for just three months. Furthermore, it is more than offset by the sustained fall in shipments that occurs from month four to month 24. Over these longer horizons, high NO/S mean reverts because new orders fall even faster than shipments, not because shipments rise to match new orders.

Table 2
NO/S and the macroeconomy

#	Intercept	$\Delta \ln NO_t$	$\Delta \ln S_t$	$\Delta \ln GDP_t$	$\Delta \ln GDP_{t-4}$	$\Delta \ln C_t$	$\Delta \ln I_t$	$\Delta \ln N_t$	$RMRF_t$	Term $Spread_t$	T-Bill $Rate_t$	Adjusted R-squared
1	0.013	0.194										0.234
	(3.453)	(5.868)										
2	0.012		0.250									0.195
	(3.038)		(4.618)									
3	0.014	0.236	−0.062									0.231
	(3.568)	(3.141)	(−0.566)									
4	−0.006			0.737								0.197
	(−0.911)			(4.661)								
5	−0.014			0.697	0.305							0.223
	(−1.826)			(4.915)	(2.411)							
6	−0.007					1.255						0.183
	(−1.037)					(5.404)						
7	−0.006					0.869	0.067	0.142				0.195
	(−0.876)					(2.497)	(1.006)	(0.902)				
8	0.015								0.065			0.081
	(2.985)								(2.844)			
9	0.016								0.055	−4.923	6.062	0.182
	(3.826)								(2.713)	(−1.517)	(1.631)	

This table displays regressions in which the dependent variable is $\ln NO/S_{t+1}$, where NO and S denote new orders and shipments, respectively, of durable goods. Explanatory variables include past growth rates in durable new orders and shipments, GDP, consumption (C), fixed investment (I), and inventories (N), in addition to the excess stock market return (RMRF), the term spread, and the T-bill rate. All growth rates are computed over four quarters, e.g., $\Delta \ln GDP_t = \ln GDP_t - \ln GDP_{t-4}$. Excess market returns are also computed over four quarters. All quantity data are real and seasonally adjusted, and the sample is from 1958Q2 to 2009Q4. Newey-West t-statistics in parentheses use 8 lags.

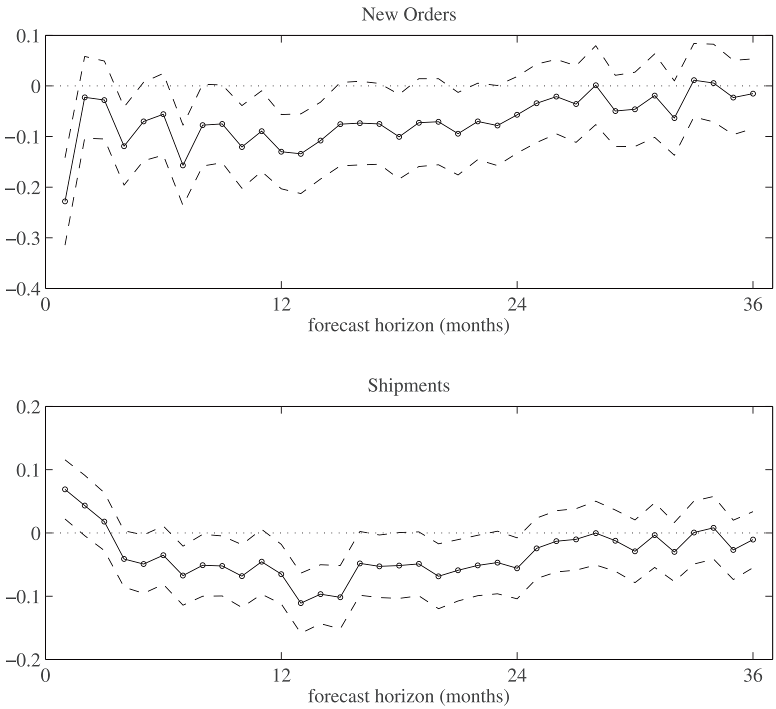

Figure 2
Predicting new orders and shipments growth using NO/S
Each panel of this figure plots the slope coefficients and 95% confidence intervals from the regression of the growth rate of NOor Son lagged ln NO/S, i.e.,

$$\ln Y_{t+\tau} - \ln Y_{t+\tau-1} = \alpha + \beta \ln NO/S_t + \epsilon_t.$$

where Y denotes either real new orders or real shipments of durable goods. Values of τ are given on the horizontal axis, denoting the forecast horizon in months. Newey-West standard errors are computed using one lag. Data are monthly from 2/1958 to 12/2009.

We next examine the relationship between NO/S and two more standard measures of economic output, namely GDP and corporate earnings. The top panel of Figure 3 plots the correlations between ln NO/S and growth rates of GDP and earnings at various leads and lags. The bottom panel shows correlations between ln NO/S and the detrended levels of GDP and earnings, where we use the Hodrick and Prescott (1997) filter for detrending. To remove the seasonality in earnings, we analyze four-quarter moving averages.

We find that NO/S slightly lags the growth rates of both GDP and earnings but slightly leads their levels. The contemporaneous correlations with the detrended GDP and earnings levels are about 0.6 and 0.5, respectively, confirming earlier visual evidence that NO/S is strongly procyclical. High levels of NO/S indicate an impending business cycle peak, as growth rates in both variables are

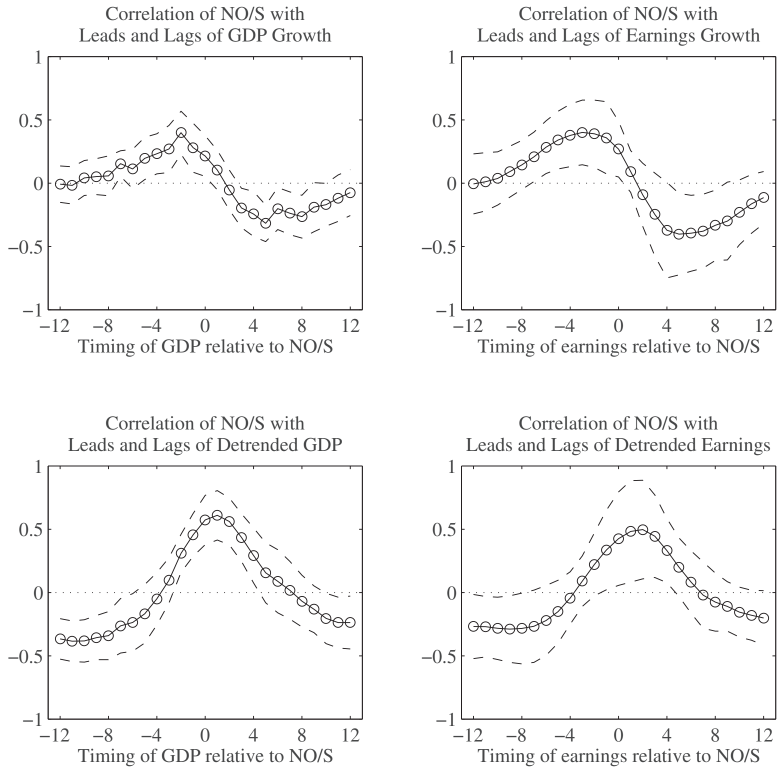

Figure 3
Correlations of NO/S with leads and lags of GDP and earnings
The top panels of this figure show correlations between NO/S at the end of quarter t and the growth rates of GDP and corporate earnings in quarter $t+\tau$, where τ is the value on the x-axis. The bottom panels show the correlations between NO/S in quarter t and the detrended levels of GDP and earnings in quarter $t+\tau$. Quarterly data are used for the GDP results, while four-quarter moving averages are used for earnings to account for seasonality. The sample is from 1958Q2 to 2009Q4. Detrending is performed using the Hodrick-Prescott (1997) filter with a bandwidth of 1600. Newey-West standard errors are calculated using six lags for GDP growth, eight lags for the detrended level of GDP, eight lags for earnings growth, and 10 lags for the detrended level of earnings.

positively related to NO/S in the very short run but negatively related to NO/S at horizons of one to two years.

The remaining results in Table 2 use alternative explanatory variables related to the business cycle. These include growth rates in GDP, consumption, fixed investment, and inventories, in addition to the term spread, the T-bill rate, and the excess stock market return. All growth rates and market returns are computed over four quarters.

Regressions 4 and 5 again demonstrate that NO/S is procyclical, with high NO/S generally following periods of positive GDP growth. Growth over the most recent four quarters is particularly relevant, explaining 20% of the variation in ln NO/S. The coefficient on GDP growth between eight quarters and four quarters ago is about half the size and contributes modestly to the regression R-square.

Regression 6 replaces GDP growth with consumption growth. The resulting regression fit is similar, suggesting that the consumption component of GDP is most responsible for its relation to NO/S. This is confirmed in regression 7, which also includes the growth rates of fixed investment and inventories. Neither of these variables is significant.

In regressions 8 and 9, we examine financial market predictors of ln NO/S. Regression 8's sole explanatory variable is the excess stock market return over the previous four quarters. The coefficient is positive and significant, implying that NO/S is also procyclical in its relation to asset prices. In regression 9, we also include the term spread and the T-bill rate, variables that are considered to be countercyclical and procyclical, respectively. The significance of both coefficients is marginal, but the signs are again consistent with the conclusion that NO/S is procyclical.

In untabulated results, we also considered the effects that changing terms of trade might have on NO/S. Using the real effective exchange rate index from the Bank for International Settlements over a sample starting in October 1963, we find that NO/S is higher when the value of the dollar has declined over the previous twelve months. This is consistent with cheaper dollars making durable goods purchases from U.S. manufacturers more attractive. Including this variable in any of the regressions in Table 2 did not substantially alter any of the other coefficient estimates.

2.2 Predicting economic activity with NO/S

We have shown that NO/S is significantly related to future shipments of durable goods, GDP growth, and earnings growth. We now seek to establish whether other measures of economic output are similarly predictable, and also whether ln NO/S retains its significance as a predictor of future output growth when other control variables are included.

Evidence for predictability in GDP, per capita consumption, and equipment investment is presented in Figure 4. These plots use the same regression approach as Equation (1) and Figure 2. Non-overlapping one-quarter growth rates are regressed on lagged ln NO/S, and the slope coefficients and their confidence intervals are graphed as a function of the forecast horizon.

Mirroring the results in Figure 3, high NO/S forecasts a long-run decline in GDP after a short but insignificant rise. The same long-run effect is seen in consumption growth, but the short-run effect is absent. Both of these effects die off after about three years.

In contrast, equipment investment rises significantly following high NO/S with approximately a three-month lag. In our sample period, the average ratio of unfilled orders to shipments is 3.3, suggesting that the average order is filled in roughly 3.3 months. Thus, the length of this surge of investment may not

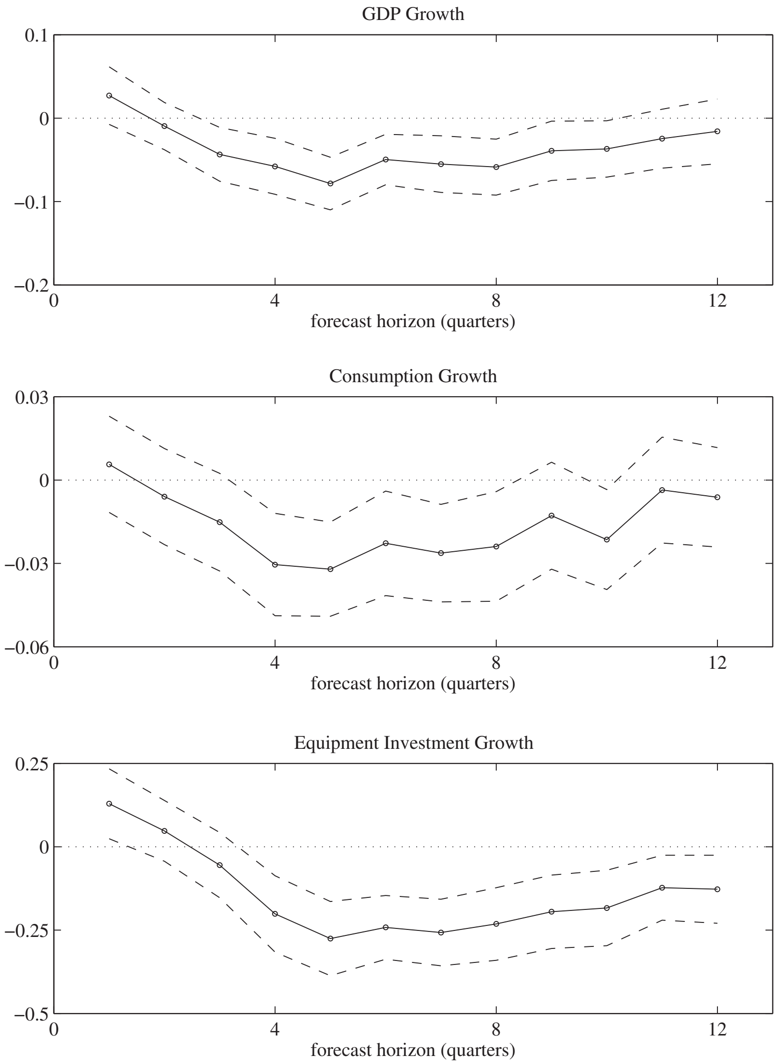

Figure 4
Predicting GDP and components using NO/S
Each panel of this figure plots the slope coefficients and 95% confidence intervals from the regression of some macro growth measure on lagged ln NO/S, i.e.,

$$\ln Y_{t+\tau} - \ln Y_{t+\tau-1} = \alpha + \beta \ln NO/S_t + \epsilon_t,$$

where Y denotes either real GDP, per capita consumption, or equipment investment. Values of τ are given on the horizontal axis, denoting the forecast horizon in quarters. Newey-West standard errors are computed using one lag. Data are quarterly from 1958Q2 to 2009Q4.

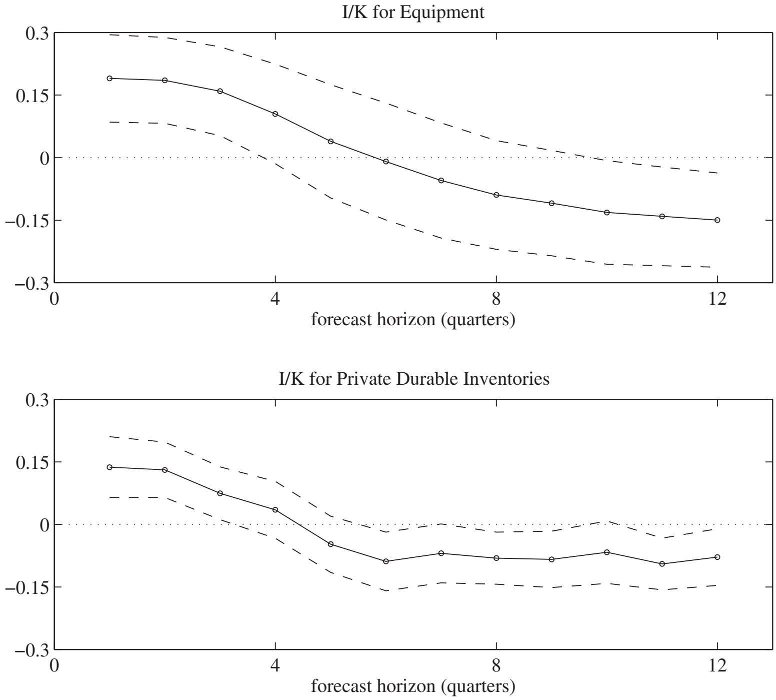

Figure 5
Predicting investment/capital ratios using NO/S
Each panel of this figure plots the slope coefficients and 95% confidence intervals from the regression of some investment/capital ratio on lagged ln NO/S, i.e.,

$$\frac{I_{t+\tau}}{K_{t+\tau}} = \alpha + \beta \ln NO/S_t + \epsilon_t,$$

where I and K denote investment and capital stock in either equipment or private durable inventories. Values of τ are given on the horizontal axis, denoting the forecast horizon in quarters. Newey-West standard errors are computed using one lag. Data are quarterly from 1958Q2 to 2009Q4.

be far from the amount of time it takes for newly ordered durable goods to be shipped.

Figure 5 shows that while NO/S is positively related to investment growth for just one or two quarters, its relation with investment-capital ratios is positive for a much longer period. We observe this for equipment investment and private durable inventory investment, which are the two most natural outcomes resulting from the shipment of durable goods.[10] Thus, even though investment growth slows following high NO/S, the level of investment in the economy remains robust.

[10] Private durable inventory investment, defined as the change in inventories, may take negative values. We are therefore unable to analyze its growth rate, as we did with other variables in Figure 4.

Table 3 examines whether the ability of NO/S to predict future GDP growth is robust to the inclusion of the term spread, the Treasury bill rate, and the past growth rate of GDP or new orders. It is well known (e.g., Harvey 1989; Stock and Watson 1989) that the slope of the term structure forecasts future GDP, in particular, that upward-sloping term structures forecast higher GDP growth. Both Ang, Piazzesi, and Wei (2006) and Wright (2006) demonstrate that the level of the term structure also contains useful information about future output growth, so we include the Treasury bill rate as a proxy for the term structure level. Since Ang, Piazzesi, and Wei (2006) also find that lagged GDP growth is an important predictor, we include this variable as well. We compare it to the lagged growth in new orders, a variable that is often cited in the popular press as providing an indication of future economic growth.

We examine the predictive power of NO/S at a number of different forecast horizons. Following the earlier observations that one-quarter-ahead GDP is weakly positively related to NO/S and two-quarter-ahead GDP has little relation to NO/S, we consider separate forecasts of these two quarters. We then forecast GDP growth three and four quarters ahead and between five and eight quarters ahead to capture longer horizon predictability.

The regression results in Table 3 demonstrate that the univariate significance of ln NO/S for longer horizon forecasts of GDP growth persists after controlling for the other variables.[11] We continue to find no significant relation between NO/S and output growth at shorter horizons, though we note that at a one-quarter horizon GDP is strongly forecastable using the growth in new orders, even after controlling for lagged GDP growth. The growth in new orders is often used in the popular press as a leading indicator, and our results support this interpretation. The only caveat is that the predictive power of this variable is solely at the shortest horizons.

In order to examine short-run output predictability in more detail, we perform similar regressions in which the dependent variable is the growth rate in industrial production (IP). Since IP is available on a monthly basis, it is possible to use it to gauge the short-run effects of NO/S. Higher-frequency regressions are also useful for checking whether our short-horizon GDP growth regression results are driven by time aggregation bias, which arises when the decision frequency is higher than the observation frequency. Marcet (1991) suggests that the econometrician who suspects that time aggregation is a potential problem “should look for data collected at a finer interval.” This is made possible by examining IP instead of GDP.

In Table 4, we examine horizons of one, two, and three months and find that NO/S strongly predicts the IP growth rate at a one-month horizon. At two months, some predictability is still evident, but it disappears in month three.

[11] We also computed t-statistics for long-horizon forecasts using the Hodrick (1992) approach. These were significantly larger, most likely because the Hodrick method does not account for serial correlation in the short-horizon forecast errors, which is sizable in GDP growth rates.

Table 3
Predictability in GDP growth rates

Intercept	ln NO/S	Term Spread	T-Bill Yield	Lag GDP Growth	Lag NO Growth	Adjusted R-Squared
			GDP growth from t to $t+1$			
0.007	0.027					0.009
(8.361)	(1.410)					
0.006	0.024	0.819	−0.411	0.307		0.121
(2.445)	(1.245)	(1.160)	(−1.167)	(3.152)		
0.007	−0.011	0.187	−0.302	0.179	0.064	0.204
(3.256)	(−0.538)	(0.252)	(−0.902)	(2.135)	(4.244)	
			GDP growth from $t+1$ to $t+2$			
0.008	−0.010					−0.003
(9.634)	(−0.546)					
0.006	−0.002	1.531	−0.465	0.259		0.113
(2.566)	(−0.078)	(1.981)	(−1.194)	(2.633)		
0.007	−0.018	1.247	−0.421	0.199	0.030	0.127
(3.157)	(−0.647)	(1.545)	(−1.096)	(2.295)	(1.641)	
			GDP growth from $t+2$ to $t+4$			
0.017	−0.102					0.069
(11.584)	(−2.780)					
0.015	−0.088	1.900	−0.552	0.237		0.112
(3.021)	(−1.921)	(1.241)	(−0.681)	(1.633)		
0.017	−0.120	1.351	−0.479	0.116	0.059	0.135
(3.539)	(−2.262)	(0.847)	(−0.598)	(1.027)	(2.248)	
			GDP growth from $t+4$ to $t+8$			
0.035	−0.241					0.143
(12.938)	(−3.612)					
0.034	−0.194	3.423	−0.366	−0.188		0.153
(3.428)	(−3.016)	(1.331)	(−0.243)	(−0.772)		
0.034	−0.219	2.989	−0.258	−0.262	0.043	0.153
(3.573)	(−2.937)	(1.182)	(−0.169)	(−1.057)	(1.258)	

This table contains the results of restricted versions of the regression:

$$\ln GDP_{t+\tau_2} - \ln GDP_{t+\tau_1} = \beta_0 + \beta_1 \ln NO/S_t + \beta_2 TERM_t + \beta_3 TBILL_t + \beta_4 \Delta \ln GDP_t + \beta_5 \Delta \ln NO_t + \epsilon_t$$

for various values of τ_1 and τ_2. GDP is real and seasonally adjusted, TERM is the difference between 10-year and 3-month Treasury yields, and TBILL is the yield on a 3-month Treasury bill. Values in parentheses are t-statistics computed using Newey-West standard errors. The number of lags used in the four panels of the table are 1, 1, 3, and 6, respectively. Data are quarterly from 1958Q2 to 2009Q4.

These results reinforce the conclusion, drawn from Figure 2, that high NO/S foretells an imminent business cycle peak, with predicted output growth that is higher in the very short run but lower for longer horizons.

We find marginal evidence that the level and slope of the term structure predict higher output growth, but these effects are limited to short horizons and are not very robust. Lagged output growth is often highly significant, but only in the first two quarters.

Overall, the relationships we observe between NO/S and future output growth are complex and clearly inconsistent with the conventional wisdom that a high ratio indicates "a good business outlook." Only at the shortest horizons does

Table 4
Short-run predictability in industrial production growth rates

Intercept	ln NO/S	Term Spread	T-Bill Yield	Lag IP Growth	Lag NO Growth	Adjusted R-Squared
			IP growth from t to $t+1$			
0.002	0.048					0.038
(2.707)	(3.441)					
0.002	0.037	0.545	−0.275	0.336		0.161
(1.328)	(3.431)	(1.852)	(−1.455)	(6.378)		
0.002	0.033	0.501	−0.268	0.327	0.008	0.160
(1.428)	(2.886)	(1.673)	(−1.409)	(6.280)	(0.671)	
			IP growth from $t+1$ to $t+2$			
0.002	0.032					0.016
(3.115)	(2.267)					
0.002	0.032	0.680	−0.403	0.197		0.077
(1.646)	(2.177)	(1.770)	(−1.690)	(2.855)		
0.003	0.026	0.596	−0.392	0.180	0.016	0.079
(1.779)	(1.576)	(1.496)	(−1.642)	(2.842)	(0.997)	
			IP growth from $t+2$ to $t+3$			
0.002	0.020					0.005
(3.524)	(1.274)					
0.003	0.023	0.863	−0.470	0.185		0.073
(1.737)	(1.261)	(2.107)	(−1.864)	(2.035)		
0.003	0.015	0.747	−0.455	0.162	0.022	0.078
(1.891)	(0.750)	(1.782)	(−1.824)	(1.759)	(1.505)	

This table contains the results of restricted versions of the regression

$$\ln IP_{t+\tau_2} - \ln IP_{t+\tau_1} = \beta_0 + \beta_1 \ln NO/S_t + \beta_2 TERM_t + \beta_3 TBILL_t + \beta_4 \Delta \ln IP_t + \beta_5 \Delta \ln NO_t + \epsilon_t$$

for various values of τ_1 and τ_2. IP is real and seasonally adjusted, TERM is the difference between 10-year and 3-month Treasury yields, and TBILL is the yield on a 3-month Treasury bill. Values in parentheses are t-statistics computed using Newey-West standard errors with one lag. Data are monthly from 2/1958 to 12/2009.

this conventional wisdom have any validity. At longer horizons, high NO/S is clearly associated with gradual economic decline.

3. Discussion

The previous section provided clear evidence that NO/S is procyclical, tending to reach its peak just prior to that of the business cycle. NO/S is strongly positively related to the past two years of GDP growth, and among the different components of GDP it is particularly related to past consumption growth. These empirical observations are consistent with a simple economy where cycles are generated by an exogenous productivity shock. Following a good productivity shock (boom), economic output will rise, and agents will optimally increase both consumption and investment. If investment is not instantaneous, however, and investment goods must be ordered in advance, then new orders of investment goods will respond to productivity shocks immediately, whereas actual investment will respond with a lag. Hence, new orders would be strongly procyclical as well.

The procyclicality of NO/S would be reinforced if discount rates move over the business cycle in a countercyclical fashion. Following Abel and Blanchard (1986), a countercyclical cost of capital creates an additional incentive to increase investment during booms, at both the corporate and household levels. New orders for investment goods would therefore rise even further, and since shipments of such goods respond with a lag, we see a high NO/S that predicts subsequent short-term investment growth.

The relationship between NO/S and investment growth described in Figure 4 reveals another pattern, however, namely a negative long-run relationship between NO/S and investment growth. Lettau and Ludvigson (2002) argue that Q theory implies a positive long-run relation between investment growth and the cost of capital. Thus, if variation in NO/S reflects, to some extent, countercyclical risk premia, then it is possible that high NO/S would predict declining investment at longer horizons.

If countercyclical risk premia are reflected in NO/S, then the recent asset pricing literature suggests a number of possible underlying mechanisms. In one, the external habit model of Campbell and Cochrane (1999), prolonged consumption growth raises the "surplus consumption ratio," a measure of how far current consumption is from the habit level. When the surplus consumption ratio is high, aggregate risk aversion falls, leading to a decline in market-wide risk premia. In another, the long-run risk model of Bansal and Yaron (2004), it is conditional heteroskedasticity in consumption growth that drives risk premia. When economic uncertainty is high, expected returns are also high.[12] A number of other models might be consistent with our findings as well.[13]

In our data, we observe that NO/S tends to be high following periods of positive consumption growth, but we have not yet compared NO/S to surplus consumption per se. Nor did we examine whether NO/S is related to consumption volatility. We turn to these issues in Table 5. In this table, we regress NO/S on the contemporaneous consumption surplus, consumption volatility, and S&P 500 Index return volatility. The consumption surplus is computed by applying the Campbell-Cochrane habit model to our per capita consumption series using the parameter values reported in their paper. Consumption volatility is computed using the VAR-GARCH model of Bansal, Khatchatrian, and Yaron (2005), which applies a GARCH(1,1) model to the errors of an AR(1) process for quarterly consumption growth. Finally, the

[12] The Bansal and Yaron (2004) model does not formally generate countercyclical risk premia since there is no correlation between the consumption growth and volatility processes. They note, however, that consumption volatility tends to be high during recessions. An extension of their model that adds this correlation would presumably generate countercyclical premia.

[13] 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 time-varying cross-sectional distribution of labor income; in Guvenen (2009) from limited participation; and in Piazzesi, Schneider, and Tuzel (2007) from time-varying consumption composition risk. Kuehn (2008) generates endogenous predictability within a general equilibrium model featuring Epstein-Zin preferences and investment commitments.

Table 5
NO/S and theory-implied risk premia determinants

#	Intercept	Surplus Consumption$_t$	Consumption Volatility$_t$	S&P 500 Volatility$_t$	Adjusted R-squared
1	0.135	0.042			0.128
	(4.702)	(4.297)			
2	0.031		−3.447		0.004
	(1.797)		(−0.830)		
3	0.039			−2.550	0.097
	(4.552)			(−3.210)	
4	0.140	0.033	−3.571	−1.789	0.172
	(4.584)	(2.893)	(−1.033)	(−2.912)	

This table displays regressions in which the dependent variable is $\ln NO/S_{t+1}$. Explanatory variables include the surplus consumption ratio computed using the model of Campbell and Cochrane (1999), consumption volatility computed from the VAR-GARCH model of Bansal, Khatchatrian, and Yaron (2005), and an S&P 500 volatility computed from daily index returns. Newey-West t-statistics in parentheses use eight lags.

volatility of the S&P 500 Index, an alternative measure of economic uncertainty, is computed as the standard deviation of the most recent 12 months of daily returns.

The results in Table 5 are fairly clear that NO/S has a significant relation to the consumption surplus and to stock return volatility, but not to the volatility of consumption. The first result is consistent with external habit being a driver of variation in NO/S. The lack of a relation between NO/S and consumption volatility has several possible interpretations. One is that consumption volatility, to the extent that it is related to risk premia, captures a component that is more persistent than the one proxied by NO/S. This is supported by the fact that the estimated autocorrelation of the consumption volatility process is about 0.89 at the quarterly frequency, which is much more persistent than NO/S. Another possibility is that consumption volatility, because of its reliance on quarterly data, is too poorly measured for its effects to be detected. This might explain why stock market volatility, being more precisely estimated due to the use of daily data, has a more significant effect. Alternatively, stock price volatility might have little to do with consumption volatility and more to do with changing risk aversion, as is implied by the Campbell and Cochrane model. Our results cannot distinguish between these possibilities.

In sum, NO/S is significantly related to several variables that drive risk premia under standard asset pricing models. A relation with risk premia might also help explain the negative long-run relationship between NO/S and investment growth. To address these issues directly, the next section examines the relation between NO/S and risk premia using a standard predictive regression approach.

4. Return Predictability

4.1 In-sample analysis

We begin this section by asking whether there is return predictability related to NO/S and whether it is robust to the inclusion of standard predictive variables.

Table 6
Correlation matrix of predictive variables

	ln NO/S	Output Gap	*cay*	Dividend Yield	Tent	Default Spread	Detrended T-Bill	I/K	Term Spread
ln NO/S	1.000	0.393	−0.304	0.016	−0.253	−0.419	0.406	0.279	−0.399
Output Gap	0.393	1.000	−0.597	−0.321	−0.435	−0.195	0.322	0.733	−0.548
cay	−0.304	−0.597	1.000	0.109	0.350	−0.017	−0.167	−0.237	0.316
Dividend Yield	0.016	−0.321	0.109	1.000	0.262	−0.057	−0.010	−0.074	0.013
Tent	−0.253	−0.435	0.350	0.262	1.000	0.124	−0.374	−0.138	0.564
Default Spread	−0.419	−0.195	−0.017	−0.057	0.124	1.000	−0.517	−0.115	0.459
Detrended T-Bill	0.406	0.322	−0.167	−0.010	−0.374	−0.517	1.000	0.152	−0.544
I/K	0.279	0.733	−0.237	−0.074	−0.138	−0.115	0.152	1.000	−0.530
Term Spread	−0.399	−0.548	0.316	0.013	0.564	0.459	−0.544	−0.530	1.000

This table contains the correlation matrix of the eight variables used in our predictive return regressions. In addition to the variables described in Tables 1 and 3, these include the output gap measured using the approach of Cooper and Priestley (2009); the dividend yield, or the most recent four quarters of dividends divided by the current level of the S&P Composite; the *cay* variable from Lettau and Ludvigson (2001); the default spread, measuring the difference between BAA and Treasury yields; the "tent" factor from Cochrane and Piazzesi (2005); the detrended 3-month T-bill rate; and the investment-capital ratio (I/K) of Cochrane (1991). In order to account for reporting delays, the macro-based variables (ln NO/S, the output gap, *cay*, and I/K) are lagged one month relative to the other predictors. All correlations are computed from monthly data from 2/1958 to 12/2009. *cay* and I/K, which are only available quarterly, are converted to monthly by filling in the first two months of the quarter with the previous quarter's value.

Most of the variables used in our predictive regressions are fairly standard. They consist of the dividend yield, the default spread, the output gap measure of Cooper and Priestley (2009), the most recent quarter-end value of Lettau and Ludvigson's (2001) *cay* variable, Cochrane and Piazzesi's (2005) "tent" factor, and the detrended three-month T-bill yield of Fama and Schwert (1977). In all the return regressions, we follow Cooper and Priestley (2009) by lagging the macro-based predictors (ln NO/S, the output gap, and *cay*) by an extra month to ensure that their values would have been known before the beginning of the holding period. All other predictors would generally be observable in real time.

Table 6 contains the correlation matrix of the variables in our predictive regressions in addition to the term spread and the investment-capital ratio of Cochrane (1991).[14] The correlations between ln NO/S and the output gap, the term spread, and the default spread are all consistent with NO/S being procyclical, but all of these correlations are below 0.42 in absolute value, indicating that the information that NO/S provides is not redundant.

Tables 7-A to E contain our results on forecasting the excess returns to various asset classes. The excess return is defined as the difference between the continuously compounded rate of return on an asset and the continuously compounded one-month T-bill rate. All data are monthly, and forecasts of returns at the one-quarter and one-year horizon are based on overlapping sums of one-month excess returns. Standard errors are computed using the Hodrick (1992) procedure, which Ang and Bekaert (2007) argue has better small sample

[14] Including the term spread and the investment-capital ratio in our regressions does not change any results substantially, as these variables are generally insignificant in the presence of our other regressors.

Table 7-A
Predictability in excess stock market returns

Intercept	ln NO/S	Output Gap	*cay*	Dividend Yield	Tent	Default Spread	Detrended T-Bill	Adjusted R-Squared
				Return during first month				
0.005	−0.108							0.006
(2.654)	(−1.957)							
0.006		−0.053	0.231	0.242	−0.174	−2.404	−6.479	0.028
(0.743)		(−1.447)	(1.704)	(1.187)	(−1.723)	(−0.597)	(−2.312)	
0.007	−0.034	−0.049	0.218	0.252	−0.177	−2.942	−6.276	0.027
(0.844)	(−0.530)	(−1.338)	(1.591)	(1.240)	(−1.757)	(−0.705)	(−2.213)	
				Return during first quarter				
0.017	−0.461							0.040
(3.064)	(−3.213)							
0.007		−0.144	0.807	0.779	−0.475	−2.521	−11.780	0.073
(0.319)		(−1.364)	(2.097)	(1.312)	(−1.791)	(−0.223)	(−1.677)	
0.018	−0.345	−0.107	0.677	0.886	−0.498	−7.984	−9.699	0.088
(0.770)	(−2.173)	(−0.998)	(1.759)	(1.489)	(−1.882)	(−0.686)	(−1.382)	
				Return during first year				
0.062	−1.503							0.100
(2.911)	(−3.185)							
−0.033		−0.139	3.350	2.811	−0.081	−9.242	−19.031	0.187
(−0.402)		(−0.360)	(2.505)	(1.320)	(−0.103)	(−0.289)	(−0.861)	
0.001	−1.191	−0.028	2.921	3.202	−0.213	−24.082	−10.770	0.232
(0.013)	(−2.222)	(−0.071)	(2.251)	(1.501)	(−0.274)	(−0.704)	(−0.472)	

This table contains results from regressing future excess stock returns on macroeconomic and financial predictive variables. The excess return is defined as the difference between the continuously compounded return on the CRSP value-weighted index and the contemporaneous return on a 1-month Treasury bill. Returns during the first quarter and first year are overlapping sums of the first 3 or 12 monthly returns following the forecast date. All predictive variables are described in Tables 1, 3, and 6. Values in parentheses are t-statistics computed from Hodrick's (1992) standard errors. Data are from 2/1958 to 12/2009.

performance than the Newey and West (1987) or Hansen and Hodrick (1980) methods, with only a slight tendency to under-reject.

Table 7-A indicates that NO/S has significant predictive ability for excess market returns at horizons from one quarter to one year. In particular, lower levels of NO/S are associated with higher excess returns. The magnitude of the effect is sizable as well. Without controlling for other variables believed to predict stock returns, a one-standard-deviation (0.0362) decrease in ln NO/S raises the one-year expected excess return by 5.4%. Even after adding the other controls, the effect on excess returns is still 3.8%. R-squares from these univariate regressions range from 0.6% for monthly returns to 10% for annual returns. Little predictability is observed past the first year, at least after including other controls, so we do not report these results here.

We note that while the 10% R-squared is large, it is nevertheless below the theoretical R-squared in a dividend yield regression under the Campbell and Cochrane (1999) model, a value that is calibrated to match

Table 7-B
Predictability in excess long-term Treasury bond returns

Intercept	ln NO/S	Output Gap	*cay*	Dividend Yield	Tent	Default Spread	Detrended T-Bill	Adjusted R-Squared
				Return during first month				
0.002	−0.055							0.003
(1.481)	(−1.786)							
−0.002		−0.002	0.067	−0.064	0.089	1.295	−0.028	0.001
(−0.356)		(−0.106)	(0.696)	(−0.436)	(0.948)	(0.396)	(−0.014)	
−0.001	−0.029	0.001	0.057	−0.055	0.087	0.841	0.143	0.000
(−0.203)	(−0.783)	(0.040)	(0.580)	(−0.371)	(0.929)	(0.251)	(0.068)	
				Return during first quarter				
0.006	−0.159							0.013
(1.537)	(−1.984)							
−0.005		−0.025	0.019	−0.498	0.522	3.694	4.019	0.055
(−0.326)		(−0.407)	(0.069)	(−1.228)	(2.287)	(0.446)	(0.720)	
−0.003	−0.088	−0.016	−0.015	−0.470	0.516	2.304	4.549	0.057
(−0.161)	(−0.999)	(−0.245)	(−0.055)	(−1.145)	(2.266)	(0.272)	(0.807)	
				Return during first year				
0.025	−0.580							0.044
(1.784)	(−2.250)							
−0.002		−0.089	0.030	−2.259	2.096	7.610	1.371	0.294
(−0.038)		(−0.424)	(0.033)	(−1.449)	(3.297)	(0.344)	(0.077)	
0.000	−0.061	−0.084	0.007	−2.239	2.089	6.844	1.798	0.294
(−0.008)	(−0.192)	(−0.378)	(0.008)	(−1.424)	(3.308)	(0.291)	(0.098)	

This table contains results from regressing future excess long-term Treasury bond returns on macroeconomic and financial predictive variables. The excess return is defined as the difference between the continuously compounded return on the Ibbotson long-term Treasury index and the contemporaneous return on a 1-month Treasury bill. Returns during the first quarter and first year are overlapping sums of the first 3 or 12 monthly returns following the forecast date. All predictive variables are described in Tables 1, 3, and 6. Values in parentheses are t-statistics computed from Hodrick's (1992) standard errors. Data are from 2/1958 to 12/2009.

their data sample.[15] This implies that risk premia in their model exhibit greater variation than the risk premia we obtain as fitted values from our regression. A key difference between the fitted values from our regression and the risk premia forecasts from their model is that our fitted values are not restricted to be positive. It might be desirable to consider alternative specifications that impose positive risk premia, but we do not pursue this here.

At the quarterly and annual horizons, the significance of NO/S is robust to the inclusion of a number of predictive variables, namely the dividend yield, *cay*, Cochrane and Piazzesi's (2005) tent factor, the default spread, the detrended Treasury bill rate, and the output gap measure of Cooper and Priestley (2009). It is notable that most of these variables are constructed from market prices, hence the endogeneity bias of Stambaugh (1999) is at least somewhat of a concern when interpreting the t-statistics for these coefficients. The exception, in addition to ln NO/S, is the output gap. Variables that are not constructed

15 Campbell and Cochrane's (1999) model generates a correlation of -.35 between the P/D ratio and the future one-year return on a consumption claim, which implies an R-squared of 12%.

Table 7-C
Predictability in excess intermediate-term Treasury bond returns

Intercept	ln NO/S	Output Gap	*cay*	Dividend Yield	Tent	Default Spread	Detrended T-Bill	Adjusted R-Squared
				Return during first month				
0.002	−0.044							0.010
(2.829)	(−2.741)							
−0.002		−0.002	0.002	−0.014	0.064	0.934	−0.007	0.005
(−0.680)		(−0.170)	(0.045)	(−0.164)	(1.354)	(0.769)	(−0.006)	
−0.001	−0.036	0.002	−0.011	−0.003	0.061	0.362	0.209	0.008
(−0.307)	(−1.786)	(0.180)	(−0.230)	(−0.035)	(1.305)	(0.290)	(0.168)	
				Return during first quarter				
0.005	−0.103							0.017
(2.715)	(−2.381)							
−0.005		−0.015	−0.077	−0.185	0.300	2.259	1.622	0.053
(−0.521)		(−0.456)	(−0.575)	(−0.766)	(3.120)	(0.696)	(0.454)	
−0.002	−0.074	−0.007	−0.105	−0.162	0.295	1.088	2.068	0.058
(−0.267)	(−1.471)	(−0.209)	(−0.793)	(−0.661)	(3.066)	(0.331)	(0.570)	
				Return during first year				
0.021	−0.329							0.044
(2.904)	(−2.194)							
−0.009		0.005	−0.110	−0.790	1.141	4.708	−2.303	0.244
(−0.274)		(0.042)	(−0.232)	(−0.821)	(3.642)	(0.472)	(−0.254)	
−0.006	−0.082	0.013	−0.139	−0.763	1.132	3.690	−1.736	0.245
(−0.205)	(−0.546)	(0.102)	(−0.298)	(−0.787)	(3.622)	(0.363)	(−0.190)	

This table contains results from regressing future excess intermediate-term Treasury bond returns on macroeconomic and financial predictive variables. The excess return is defined as the difference between the continuously compounded return on the Ibbotson intermediate-term Treasury index and the contemporaneous return on a 1-month Treasury bill. Returns during the first quarter and first year are overlapping sums of the first 3 or 12 monthly returns following the forecast date. All predictive variables are described in Tables 1, 3, and 6. Values in parentheses are t-statistics computed from Hodrick's (1992) standard errors. Data are from 2/1958 to 12/2009.

from prices should be less likely to display Stambaugh's bias, and this is particularly true for NO/S given its relatively low levels of serial correlation. Furthermore, this low autocorrelation also makes NO/S less susceptible to the spurious regression bias of Ferson, Sarkissian, and Simin (2003).

We note that the other pure macro predictor, the output gap, is not significant at any horizon with the other controls in place. The lack of robustness of the output gap as a return predictor seems surprising given the results of Cooper and Priestley (2009), but none of their regressions included *cay* as a control, as we do here. In untabulated results, we confirm Cooper and Priestly's results by finding that the significance of the output gap is robust to the inclusion of predictive variables other than *cay*. However, in regressions that include both *cay* and the output gap, only *cay* is significant.

The forecasting ability of NO/S is not limited to stock returns. Tables 7-B and 7-C report results for forecasts of excess returns on long-term and intermediate-term Treasury bonds, respectively. The coefficients on ln NO/S are smaller here than they were for equities, but they are generally significant in the univariate regressions. In contrast to the stock regressions, including controls

Table 7-D
Predictability in excess corporate bond returns

Intercept	ln NO/S	Output Gap	*cay*	Dividend Yield	Tent	Default Spread	Detrended T-Bill	Adjusted R-Squared
				Return during first month				
0.003	−0.098							0.018
(2.372)	(−3.387)							
−0.006		−0.016	0.106	0.003	0.036	3.782	−0.138	0.017
(−1.085)		(−0.881)	(1.205)	(0.018)	(0.415)	(1.230)	(−0.073)	
−0.004	−0.052	−0.010	0.087	0.019	0.033	2.959	0.174	0.020
(−0.773)	(−1.585)	(−0.560)	(0.971)	(0.131)	(0.377)	(0.941)	(0.091)	
				Return during first quarter				
0.008	−0.282							0.048
(2.464)	(−3.868)							
−0.016		−0.066	0.116	−0.274	0.365	10.149	3.809	0.070
(−1.038)		(−1.232)	(0.488)	(−0.692)	(1.677)	(1.313)	(0.741)	
−0.011	−0.171	−0.048	0.051	−0.221	0.354	7.437	4.842	0.081
(−0.681)	(−2.155)	(−0.869)	(0.213)	(−0.553)	(1.628)	(0.933)	(0.934)	
				Return during first year				
0.029	−0.856							0.102
(2.437)	(−3.340)							
−0.047		−0.119	0.311	−1.555	1.946	26.418	3.318	0.333
(−0.899)		(−0.644)	(0.395)	(−1.046)	(3.353)	(1.365)	(0.202)	
−0.039	−0.281	−0.093	0.209	−1.463	1.915	22.915	5.269	0.340
(−0.754)	(−0.896)	(−0.485)	(0.272)	(−0.976)	(3.339)	(1.094)	(0.309)	

This table contains results from regressing future excess corporate bond returns on macroeconomic and financial predictive variables. The excess return is defined as the difference between the continuously compounded return on the Ibbotson investment-grade corporate bond index and the contemporaneous return on a 1-month Treasury bill. Returns during the first quarter and first year are overlapping sums of the first 3 or 12 monthly returns following the forecast date. All predictive variables are described in Tables 1, 3, and 6. Values in parentheses are t-statistics computed from Hodrick's (1992) standard errors. Data are from 2/1958 to 12/2009.

effectively eliminates the significance of NO/S. The apparent explanation is the overwhelming significance of the tent factor. Cochrane and Piazzesi (2005) find that this factor explains over 99% of the variation in expected bond returns in their sample, meaning that there is little that is left over to be explained by other regressors.

Given its ability to predict equity and Treasury bond returns, it is natural to expect NO/S to forecast assets, like corporate bonds, that inherit characteristics of both these other asset classes. Tables 7-D and 7-E repeat the return predictability regressions using investment-grade and high-yield corporate bonds. In both of these cases, NO/S has significant forecast power at horizons from one month to one year, though the significance is only robust to the inclusion of all of the control variables in the two quarterly regressions.

In other untabulated regressions, we obtain nearly identical results if we use the earnings yield in place of the dividend yield or the term premium instead of Cochrane and Piazzesi's tent factor. Given the close links between investment and NO/S, we also ran regressions that were identical except that they also included the investment-capital ratio of Cochrane (1991). Including it

Table 7-E
Predictability in excess high-yield bond returns

Intercept	ln NO/S	Output Gap	*cay*	Dividend Yield	Tent	Default Spread	Detrended T-Bill	Adjusted R-Squared
				Return during first month				
0.004	−0.129							0.035
(3.451)	(−4.122)							
−0.008		−0.050	0.116	0.077	−0.032	5.635	−0.681	0.064
(−1.857)		(−2.912)	(1.403)	(0.645)	(−0.465)	(2.172)	(−0.464)	
−0.006	−0.048	−0.045	0.098	0.092	−0.035	4.876	−0.395	0.066
(−1.474)	(−1.399)	(−2.540)	(1.187)	(0.767)	(−0.514)	(1.850)	(−0.262)	
				Return during first quarter				
0.011	−0.398							0.080
(3.573)	(−4.661)							
−0.029		−0.139	0.427	0.230	−0.051	19.001	1.759	0.144
(−2.298)		(−2.760)	(1.855)	(0.684)	(−0.324)	(2.814)	(0.455)	
−0.023	−0.178	−0.120	0.360	0.285	−0.063	16.175	2.836	0.154
(−1.854)	(−2.126)	(−2.332)	(1.585)	(0.842)	(−0.401)	(2.371)	(0.716)	
				Return during first year				
0.039	−1.245							0.171
(3.438)	(−4.207)							
−0.097		−0.367	0.899	0.370	0.808	50.629	0.256	0.326
(−2.277)		(−2.061)	(1.161)	(0.298)	(1.602)	(2.857)	(0.018)	
−0.081	−0.562	−0.315	0.696	0.554	0.746	43.626	4.155	0.351
(−1.969)	(−1.686)	(−1.719)	(0.938)	(0.442)	(1.512)	(2.267)	(0.271)	

This table contains results from regressing future excess high-yield bond returns on macroeconomic and financial predictive variables. The excess return is defined as the difference between the continuously compounded return on the Ibbotson (Lehman/Barclays after 2005) high-yield bond index and the contemporaneous return on a 1-month Treasury bill. Returns during the first quarter and first year are overlapping sums of the first 3 or 12 monthly returns following the forecast date. All predictive variables are described in Tables 1, 3, and 6. Values in parentheses are t-statistics computed from Hodrick's (1992) standard errors. Data are from 2/1958 to 12/2009.

had little effect on the other slope coefficient estimates, and specifically almost no effect on the slope coefficients estimated for NO/S, and it was almost always insignificant.

In sum, high NO/S forecasts low returns on both stocks and bonds. For stocks, the significance of this result is robust to the inclusion of all common control variables. For bonds, adding control variables, Cochrane and Piazzesi's tent factor in particular, mostly eliminates the significance of NO/S.

Other than NO/S, the strongest predictive variables in the stock regressions are the dividend-price ratio and *cay*. Both of these variables should, in principle, reflect variation in all sources of risk premia through their dependence on market prices, yet our results clearly indicate that there is some component of risk premia that is better captured by NO/S. We believe that there are two reasons why NO/S survives the inclusion of other regressors in the stock return regression.

One is that high NO/S predicts both lower discount rates and lower corporate earnings, as shown in Figure 3. These two effects should at least partially offset each other in the valuation of the stock market.[16] Our earlier finding that changes in ln NO/S are virtually uncorrelated with stock returns also suggests that the effects may cancel each other out. As a result, changes in the factors driving NO/S do not have a large effect on stock values, and they do not get absorbed into valuation ratios like the dividend yield.

To demonstrate the second reason, we will use the log-linear approximation of Campbell and Shiller (1988), in which the log price (p_t) is linear in log dividends (d_t) and one-period discount rates ($\mu_t \equiv \mathrm{E}_t[r_{t+1}]$):

$$p_t = \text{constant} + d_t + \mathrm{E}_t \sum_{i=1}^{\infty} \rho^{i-1} (\Delta d_{t+i} - \mu_{t+i-1}).$$

Campbell and Shiller estimate the parameter ρ to be between 0.93 and 0.94 for annual data.

The approximation implies a coefficient of -1 on the current one-year discount rate μ_t. The implied coefficient on the average discount rate over the following ten years is about -7. This means that fluctuations in less persistent components of aggregate risk premia will have a relatively minor effect on asset prices, while long-term changes in discount rates will have a much greater effect. Put differently, asset prices are good for capturing persistent components of risk premia that could overpower the effects of more transient components.

NO/S is a relatively quickly mean reverting variable, so to the extent that it is a risk premia proxy it must represent a relatively transient component. It is possible, therefore, that NO/S offers incremental predictive power relative to the litany of existing predictive variables because these variables, each of which is based on the market price of some security, by their nature tend to reflect longer-term components of aggregate risk premia.

In contrast, Cochrane and Piazzesi's tent factor, which is computed from multiple security prices rather than just one, behaves much differently. Since the factor was effectively constructed to be the linear combination of bond prices that best forecast relatively short-term (one-year) returns, the tent factor seems to reflect a shorter-term component of risk premia. As a result, its ability to predict the excess returns on all four of our bond portfolios peaks at a horizon of almost exactly one year, which also happens to be the horizon at which NO/S "works" best. We note that this behavior is in stark contrast to that of the dividend yield or *cay* in stock return regressions. For the dividend yield, stock regression R-squares generally increase with the horizon to at least five to seven years. Similarly, *cay*'s predictive power for excess stock returns peaks at horizons of four to five years.

The final piece of evidence consistent with this explanation is the degree of persistence in the different predictors. Because the dividend yield and *cay*

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[16] Similarly, Lettau and Ludvigson (2005) show that high levels of *cay* forecast both high returns and high dividend growth, causing offsetting effects on the dividend yield. van Binsbergen and Koijen (2010) also find a significant positive correlation between changes in expected returns and expected dividend growth rates.

capture a more persistent component of risk premia, it makes sense that they themselves are more persistent variables. The quarterly autocorrelation of the dividend yield, for instance, is 0.97, and for *cay* it is 0.89. In contrast, the tent factor and ln NO/S are much less persistent, with quarterly autocorrelations of 0.67 and 0.57, respectively. Thus, although tent and ln NO/S are not too highly correlated, they nevertheless appear to capture the same short-term component of bond risk premia.

4.2 Out-of-sample forecasts

We now demonstrate that many of the previous in-sample results can also be obtained using an out-of-sample approach in which predictive regression coefficients are estimated using only the data that were observed prior to that prediction. We analyze quarterly returns to strike a balance between the greater explanatory power that is observed at longer horizons and the reduction in effective sample size that longer horizons entail. We consider non-overlapping returns in order to simplify the analysis. As a sensitivity check, we present results using both a five-year and a ten-year "initialization period."

Each quarter, we form forecasts of the next quarter's returns in two ways. The first is a simple sample average of past excess returns,

$$\overline{R}_t \equiv \frac{1}{t-1}\sum_{s=1}^{t-1} R_s,$$

while the second is the fitted value from a regression of excess returns on past NO/S[17], or

$$\hat{R}_t \equiv \hat{\alpha}_{t-1} + \hat{\beta}_{t-1} \ln NO/S_{t-1}.$$

The coefficients $\hat{\alpha}_{t-1}$ and $\hat{\beta}_{t-1}$ are estimated using returns up to period $t-1$.

The "R-square" measure used by Campbell and Thompson (2008) compares the relative forecast accuracy of these two approaches. It is computed as

$$1 - \frac{\mathrm{Var}\left(R_t - \hat{R}_t\right)}{\mathrm{Var}\left(R_t - \overline{R}_t\right)}.$$

Values above zero indicate that the regression approach offers superior forecasts. Again following Campbell and Thompson (2008), we also consider forecasts of excess returns that are restricted to take positive values. In this case, if either $\overline{R}_t$ or $\hat{R}_t$ is negative, we simply replace that value with zero.

In addition to R-squares, we also report *p*-values from the out-of-sample predictability test of Clark and West (2007). This test accounts for the fact

[17] The past value of NO/S used is from the *middle* of the previous quarter. Hence, there is a one-month lag between the period in which NO/S is calculated and the start of the holding period. This means that the value of NO/S would be known at the beginning of that holding period.

Table 8
Out-of-sample return predictability

	Without positivity restriction			
	R-squares		Clark-West p-value	
Initialization period	5 years	10 years	5 years	10 years
Stock market	0.0279	0.0268	0.0177	0.0230
Long-term Treasuries	0.0058	0.0061	0.0889	0.0904
Intermediate-term Treasuries	0.0098	0.0105	0.0469	0.0513
Corporate bonds	0.0437	0.0437	0.0030	0.0038
High-yield bonds	0.0857	0.0851	0.0049	0.0058
	With positivity restriction			
	R-squares		Clark-West p-value	
Initialization period	5 years	10 years	5 years	10 years
Stock market	0.0287	0.0273	0.0242	0.0336
Long-term Treasuries	−0.0029	−0.0029	0.3573	0.3573
Intermediate-term Treasuries	0.0168	0.0173	0.0705	0.0692
Corporate bonds	0.0257	0.0264	0.0193	0.0271
High-yield bonds	0.0745	0.0742	0.0193	0.0221

This table contains results from regressing non-overlapping quarterly excess returns on lagged values of ln NO/S. Following an initialization period of 5 or 10 years, one regression is run at the end of each quarter. Denote the predicted value for the following quarter's excess return as $\hat{R}_t$. When a positivity restriction is imposed, set $\hat{R}_t$ equal to zero if the predicted value is negative. Let $\overline{R}_t$ denote the sample average computed using the same excess returns data. Following Campbell and Thompson (2008), we define an "R-squared" measure as

$$1 - \frac{\mathrm{Var}\left(R_t - \hat{R}_t\right)}{\mathrm{Var}\left(R_t - \overline{R}_t\right)}.$$

Values above zero indicate that the regression approach offers superior forecasts. The table also reports p-values from the out-of-sample predictability test of Clark and West (2007). Data are from 1958Q2 to 2009Q4.

that under the null hypothesis of no predictability, the predictive regression will have a larger mean squared forecast error due to the impact of errors in parameter estimation. Clark and West demonstrate that the test statistic is close to normal, so we report only the p-values from the test.

The results in Table 8 indicate that out-of-sample NO/S-based forecasts are usually superior to forecasts computed from sample averages. With just a five-year initialization period, all R-squares are positive, whether or not the positivity constraint is imposed. Using the Clark-West (2007) test, we reject the constant mean model for stocks, investment-grade corporate bonds, and high-yield bonds with initialization periods of five and ten years. Government bond forecasts are in a number of cases significant at the 10% level as well.

The success of NO/S out of sample is notable given the conclusions of Goyal and Welch (2008). They argue that most predictive variables fail out of sample, and that common predictive models would rarely have helped an investor time the stock market on a consistent basis. Our own out-of-sample results are fairly strong, with R-squares that are often not far below their respective in-sample values. Taken together, these results provide an additional validation to our in-sample analysis.

4.3 Alternative measures of NO/S

We motivated the use of NO/S by arguing that it represents a commitment to future capital investments by businesses and households. In this section, we consider two alternative measures of NO/S that alternately relax and strengthen this interpretation. The first measure uses new orders and shipments from total manufacturing, the sum of durables and nondurables, as opposed to the durables-only series we have used thus far. The resulting NO/S series therefore contains a large category of goods, namely nondurables, that tend to be used more for consumption than investment. The second measure uses a subcategory of durable goods, capital goods excluding defense and aircraft, for both new orders and shipments. The resulting version of NO/S therefore corresponds to a "business-only" class of investment goods, and it furthermore eliminates the often volatile and lumpy aircraft industry.

Neither of these alternative NO/S series is available over our full sample. Following the discontinuation of SIC-based classifications, the Census stopped collecting new orders data for nondurables, with the rationale that lead times were so short that the distinction between new orders and shipments was unimportant. The NO/S series based on total manufacturing, which combines durables and nondurables, therefore ends in April 2001.

New orders and shipments of capital goods excluding defense and aircraft were not calculated prior to February 1968, so that NO/S series is not available for the first 10 years of our sample. Table 9 contains the results of various regressions using both NO/S series. For brevity, we report results only for three assets: equity, long-term Treasury bonds, and high-yield corporate bonds. Results for intermediate-term Treasuries and investment-grade corporates are similar to long-term Treasuries and high-yield corporates. We also do not report the values of any coefficient or t-statistic other than the one on the NO/S series being investigated.

Overall, we find that using each alternative measure of NO/S results in similar conclusions about the sign and significance of the coefficient, though coefficient magnitudes vary somewhat. In a number of cases, the alternative measures produce stronger results. For the NO/S series constructed from total manufacturing goods, this is due to the use of a different sample period. For capital goods excluding defense and aircraft, the stronger results are not due to the sample period and therefore are likely the result of these particular goods being more sensitive to the cost of capital. Thus, it appears that the NO/S measure we focus on in this paper is not the most powerful in terms of predictive ability. Its advantage is its availability over a longer sample period.

4.4 Sector and industry results

As demonstrated recently by Gomes, Kogan, and Yogo (2009), firms in industries producing consumer durables tend to have higher returns than firms in the service sector or firms producing non-durable goods. Furthermore, expected durable returns are higher when durable expenditures are low relative to the

Table 9
Return predictability using alternative measures of NO/S

	Total manufacturing (1958-2001)						Capital goods excluding defense & aircraft (1968-2009)					
	Without controls			With controls			Without controls			With controls		
	ln NO/S			ln NO/S			ln NO/S			ln NO/S		
	Coef	*t*-Stat	R^2	Coef	*t*-Stat	R^2	Coef	*t*-Stat	R^2	Coef	*t*-Stat	R^2
						Stocks						
M	−0.257	−2.203	0.010	−0.025	−0.188	0.047	−0.119	−3.050	0.020	−0.099	−1.995	0.029
Q	−0.922	−3.349	0.048	−0.469	−1.570	0.127	−0.374	−3.974	0.062	−0.365	−3.354	0.101
A	−2.780	−3.652	0.118	−1.627	−3.380	0.342	−1.029	−3.516	0.112	−0.841	−2.840	0.230
						Long-term Treasury bonds						
M	−0.151	−2.599	0.009	−0.122	−1.634	0.011	−0.067	−2.776	0.014	−0.070	−2.056	0.007
Q	−0.426	−2.826	0.026	−0.357	−2.183	0.085	−0.148	−2.377	0.025	−0.118	−1.396	0.061
A	−1.375	−3.153	0.065	−0.650	−1.466	0.375	−0.450	−3.062	0.062	−0.070	−0.348	0.301
						High-yield bonds						
M	−0.205	−3.200	0.028	−0.049	−0.662	0.070	−0.104	−3.656	0.049	−0.048	−1.266	0.068
Q	−0.597	−3.443	0.062	−0.213	−1.261	0.149	−0.313	−3.849	0.107	−0.165	−1.834	0.165
A	−2.067	−4.889	0.156	−0.697	−1.880	0.472	−0.860	−4.840	0.181	−0.254	−1.390	0.365

This table replicates previous results using two alternative measures of NO/S. The first uses total manufacturing, which includes both durables and nondurables, for the NO and S measures. Since the nondurable new orders series ends in April 2001, that is the last month of the sample. The second uses capital goods excluding defense and aircraft for NO and S. This series is not available before February 1968.

stock of durable goods. They interpret these results as being consistent with the greater riskiness of the durable goods sector, which generates both higher unconditional expected returns and a greater responsiveness to countercyclical variation in risk premia. In this section, we examine whether NO/S predicts returns on the durable goods sector with greater accuracy by separately examining returns on durable and non-durable manufacturing.

Following the system used by the Census's M3 Survey, we classify firms according to their two-digit SIC codes. Durable manufacturing consists of SIC codes between 24 and 25 and between 32 and 39. Non-durable manufacturing consists of codes between 20 and 23 and between 26 and 31. Unlike Gomes, Kogan, and Yogo (2009), we do not distinguish firms that produce consumer products from those that produce investment goods, and we do not examine the service sector.

Based on these classifications, we compute sector returns from industry returns data provided by Kenneth French. French's categorization of firms into 38 industries corresponds to the two-digit SIC classifications above. Since his industry data includes, in addition to returns, the average market capitalization and the number of firms in each industry, we are able to compute durable and non-durable sector returns simply by computing value-weighted averages of the industry returns.

Table 10 contains results that are similar to the regression results reported earlier except that the dependent variables are now excess returns on sector portfolios. The left side of the table reports monthly, quarterly, and annual

Table 10
Stock return predictability by sector

	Without controls			With controls		
	ln NO/S			ln NO/S		
	Coef	*t*-Stat	R^2	Coef	*t*-Stat	R^2
			Non-durable manufacturing			
M	−0.075	−1.459	0.003	0.001	0.008	0.023
Q	−0.310	−2.299	0.024	−0.170	−1.129	0.071
A	−1.000	−2.298	0.058	−0.609	−1.323	0.191
			Durable manufacturing			
M	−0.116	−1.733	0.004	−0.018	−0.242	0.022
Q	−0.574	−3.345	0.036	−0.430	−2.287	0.080
A	−1.910	−3.342	0.094	−1.527	−2.322	0.188
			Durable manufacturing minus non-durable manufacturing			
M	−0.041	−1.002	0.000	−0.019	−0.417	−0.005
Q	−0.264	−2.626	0.018	−0.260	−2.561	0.028
A	−0.910	−2.881	0.046	−0.918	−2.546	0.067

This table contains slope coefficients, *t*-statistics, and R-squares from the regression of excess sector returns on lagged ln NO/S. In the left panel, ln NO/S is the sole predictive variable. On the right, all other variables used in Tables 7-A to E are included as additional controls, though the coefficients and *t*-statistics on these other variables are not reported. The non-durable manufacturing sector is defined as all firms with primary two-digit SIC codes between 20 and 23 and between 26 and 31. Durable manufacturing consists of SIC codes between 24 and 25 and between 32 and 39. "M" denotes monthly regressions, "Q" quarterly, and "A" annual. Returns for the quarterly and annual regressions are overlapping sums of the first 3 or 12 monthly returns following the forecast date. Hodrick's (1992) *t*-statistics are displayed in parentheses. Data are from 2/1958 to 12/2009.

regressions in which ln NO/S is the sole predictive variable. The right side shows results from regressions that include the other control variables used in Tables 7-A to E. To save space, the coefficients of these other variables are not displayed, nor are the intercepts shown.

Table 10 shows that NO/S, like Gomes, Kogan, and Yogo's durable expenditure-stock ratio, predicts durable goods industries more strongly than non-durable industries. The difference is large enough that the spread between durable and non-durable returns is also predictable using NO/S, especially at longer horizons. Our results are therefore consistent with the Gomes et al. finding that the greater sensitivity of durable goods producers to business cycle fluctuations makes their expected stock returns more time-varying.

A second use of industry data is to examine whether it is aggregate NO/S or industry-level NO/S that is a better predictor of industry returns. Hoberg and Phillips (2010) argue that industry boom/bust cycles, especially in competitive industries, are characterized by overvaluation and overinvestment followed by low cash flows and low returns. If the return predictability captured by NO/S is the result of overextrapolation of past trends, and if this bias has a significant industry component, then we would expect an industry's NO/S to have significant incremental power when used to forecast that industry's own returns.

Until March 2001, the Census collected new orders data for six industries, all of which are manufacturing industries that primarily produce durable goods. They are stone and glass products, primary metals, fabricated metal products,

Table 11
Aggregate vs. industry NO/S

Without controls			With controls		
Aggregate ln NO/S	Industry ln NO/S	Adjusted R-squared	Aggregate ln NO/S	Industry ln NO/S	Adjusted R-squared
−0.619 (−2.616)		0.031	−0.461 (−1.697)		0.084
	−0.158 (−1.870)	0.007		−0.113 (−1.690)	0.076
−0.633 (−2.671)	0.014 (0.248)	0.031	−0.435 (−1.610)	−0.030 (−0.690)	0.085

This table contains slope coefficients, t-statistics, and R-squares from a panel regression in which the dependent variable is the excess return on one of several industry portfolios. We include all industries for which industry-level NO/S is available, a total of six industries through 3/2001 and five industries thereafter. All industries are primarily engaged in the manufacture of durable goods. In the left panel, the only two predictive variables included are lagged aggregate ln NO/S and lagged industry ln NO/S. On the right, all other variables used in Tables 7-A to E are included as additional controls, though the coefficients and t-statistics on these other variables are not reported. All returns are quarterly and are not overlapping. Heteroskedasticity-adjusted standard errors are computed with clustering by date. Data are from 1958Q2 to 2009Q4.

non-electrical machinery, electronics, and transportation equipment. After that date, the stone and glass products series was discontinued. Each of these industries represents a single two-digit SIC code, and we match each to an industry return obtained from Kenneth French.

Table 11 reports the results of panel regressions in which the dependent variable is the non-overlapping quarterly excess return on an industry portfolio and the explanatory variables include both aggregate and industry-level ln NO/S. The left panel includes only these variables, plus an intercept that is not reported. The right panel includes the same control variables used elsewhere in the paper, whose coefficients are also unreported to save space.

Without additional controls, we find that aggregate NO/S has significant predictive power for future industry returns, but that industry-level NO/S does not. With control variables included, the statistical significance of aggregate NO/S wanes, though the coefficient is still negative, while the coefficient on industry NO/S is positive. The lack of significance seems to arise from an overly inclusive regression model. Out of the six additional control variables whose coefficients are unreported, only two are statistically significant. When we eliminate the others from the model, the significance of aggregate NO/S is restored, while the coefficient on industry-level NO/S remains positive and insignificant.

4.5 The term structure of risk premia and investment plans

We have demonstrated that NO/S predicts returns to stocks and bonds at horizons up to one year, suggesting that it reflects significant time variation in risk premia. In this section, we show that in longer horizon regressions (two to seven years), NO/S is sometimes significant as well. However, the predictive ability of NO/S over long horizons is fairly weak, and the significance of NO/S is generally lost when other common predictive variables are included. This suggests that NO/S is primarily useful as a proxy for a shorter-term component in discount rates.

An explanation for this is that the durable goods that the ratio covers are typically investments in equipment and inventories, both of which have relatively short lives. The other major type of corporate investment is in structures, such as factory buildings and offices, which have much longer economic lives. Tuzel (2010) reports that the BEA rates of depreciation for private nonresidential structures range from 1.5% to 3%, whereas the depreciation rates for private nonresidential equipment are 10%. Hence, equipment and inventory investment decisions should naturally depend primarily on short-term risk premia, while longer-term investments such as structures should respond more to changes in longer-term risk premia. An analogous ratio constructed from orders of nonresidential structures should therefore proxy for longer-term risk premia and predict asset returns at longer horizons.

In order to test this hypothesis, we construct a ratio of nonresidential building construction starts to nonresidential structures investment (Starts/SI). Construction starts (Starts) are a natural counterpart to new orders for structures investment. Measured in terms of contract award dollars, the nonresidential construction starts series tracks both private (e.g., offices and retail stores) and government buildings. Nonresidential structures investment (SI) includes both categories as well.[18]

Table 12 presents our results on forecasting the excess returns to various asset classes at horizons ranging from one month to seven years using NO/S and Starts/SI as predictive variables. Consistent with our earlier results, NO/S predicts returns of stocks and bonds at horizons up to one year. While NO/S is sometimes significant at longer horizons, its performance generally deteriorates as horizons increase beyond one year. For all assets other than long-term Treasuries, the predictive R-square is highest at the annual horizon.

In contrast, the predictive ability of Starts/SI is strongly increasing with the return horizon. In univariate regressions, the coefficient on Starts/SI is significant at long horizons and sometimes for short horizons for all assets.[19] R-squares also increase with the return horizon. At the seven-year horizon, the longest we consider, R-squares for bonds range between 0.19 and 0.35. For stocks, the R-square in the seven-year regression is 0.29.

[18] There are several differences between the coverage of the building starts and structures investment series. Building starts include the value of land, while structures investment does not. Structures investment also includes structures other than buildings, such as infrastructure. Despite these differences, the ratio is stable. Similar results are obtained when we scale building starts by other measures of structures or building investment.

[19] In untabulated results, we compute standard errors using the Newey and West (1987) method, with the number of lags equal to 1.5 times the return horizon. The resulting t-statistics are similar at the shorter horizons but uniformly larger at long horizons. At the seven-year horizon, Newey-West t-statistics on Starts/SI range from -4.0 to -6.9 for both univariate and bivariate regressions.

Table 12
Forecasting returns with NO/S and Starts/SI

	ln NO/S			ln Starts/SI			ln NO/S		ln Starts/SI		
	Coef.	*t*-stat	R^2	Coef.	*t*-stat	R^2	Coef.	*t*-stat	Coef.	*t*-stat	R^2
				Excess stock returns							
1M	−0.106	−1.889	.006	−0.027	−2.416	.008	−0.072	−1.255	−0.021	−1.847	.009
1Q	−0.459	−3.143	.039	−0.075	−2.527	.020	−0.390	−2.685	−0.044	−1.490	.044
1Y	−1.489	−3.102	.097	−0.203	−2.037	.031	−1.353	−2.711	−0.111	−1.073	.104
2Y	−1.249	−1.535	.039	−0.276	−1.535	.034	−0.984	−1.123	−0.205	−1.068	.055
3Y	−0.978	−1.002	.017	−0.458	−1.923	.076	−0.355	−0.336	−0.430	−1.681	.077
5Y	−1.881	−1.870	.047	−0.826	−2.197	.176	−0.733	−0.645	−0.768	−1.882	.182
7Y	−1.299	−1.144	.018	−1.149	−2.159	.293	0.458	0.404	−1.185	−2.119	.294
				Excess long-term Treasury bond returns							
1M	−0.054	−1.708	.003	−0.008	−1.185	.001	−0.046	−1.419	−0.005	−0.644	.002
1Q	−0.162	−1.993	.013	−0.039	−2.039	.015	−0.115	−1.394	−0.030	−1.521	.020
1Y	−0.608	−2.318	.048	−0.148	−2.260	.051	−0.466	−1.692	−0.116	−1.685	.076
2Y	−0.906	−1.838	.052	−0.279	−2.401	.089	−0.601	−1.117	−0.236	−1.867	.109
3Y	−1.261	−1.971	.065	−0.429	−2.796	.141	−0.723	−1.028	−0.372	−2.224	.159
5Y	−1.460	−1.980	.046	−0.653	−2.850	.178	−0.549	−0.668	−0.609	−2.438	.183
7Y	−1.918	−2.342	.055	−0.963	−3.160	.268	−0.556	−0.652	−0.919	−2.848	.271
				Excess intermediate-term Treasury bond returns							
1M	−0.044	−2.712	.010	−0.006	−1.676	.002	−0.040	−2.217	−0.003	−0.685	.009
1Q	−0.106	−2.392	.018	−0.025	−2.644	.020	−0.076	−1.608	−0.019	−1.869	.027
1Y	−0.345	−2.265	.048	−0.079	−2.358	.045	−0.271	−1.740	−0.061	−1.781	.072
2Y	−0.422	−1.497	.034	−0.123	−1.967	.053	−0.289	−1.018	−0.103	−1.628	.067
3Y	−0.506	−1.429	.033	−0.177	−2.129	.077	−0.281	−0.771	−0.156	−1.814	.085
5Y	−0.442	−1.240	.015	−0.261	−2.223	.109	−0.058	−0.151	−0.256	−2.043	.107
7Y	−0.641	−1.358	.025	−0.391	−2.429	.186	−0.069	−0.150	−0.386	−2.334	.184
				Excess corporate bond returns							
1M	−0.097	−3.313	.018	−0.015	−2.483	.007	−0.084	−2.823	−0.008	−1.355	.018
1Q	−0.286	−3.851	.048	−0.056	−3.464	.036	−0.227	−3.062	−0.038	−2.370	.062
1Y	−0.883	−3.387	.106	−0.159	−2.784	.061	−0.751	−2.722	−0.108	−1.796	.131
2Y	−1.231	−2.451	.097	−0.277	−2.656	.088	−0.962	−1.771	−0.207	−1.853	.142
3Y	−1.531	−2.396	.094	−0.404	−2.946	.122	−1.067	−1.544	−0.320	−2.181	.162
5Y	−1.391	−2.027	.045	−0.558	−2.788	.140	−0.632	−0.803	−0.508	−2.297	.147
7Y	−1.686	−2.239	.049	−0.853	−3.094	.244	−0.478	−0.602	−0.815	−2.796	.246
				Excess high-yield bond returns							
1M	−0.128	−3.998	.033	−0.032	−5.007	.043	−0.087	−2.790	−0.025	−4.022	.056
1Q	−0.398	−4.573	.079	−0.094	−5.431	.088	−0.285	−3.484	−0.072	−4.332	.123
1Y	−1.259	−4.186	.172	−0.276	−4.790	.147	−1.006	−3.220	−0.207	−3.480	.247
2Y	−1.625	−3.086	.143	−0.429	−4.184	.179	−1.180	−2.050	−0.344	−3.097	.247
3Y	−1.666	−2.699	.099	−0.553	−4.158	.205	−0.975	−1.417	−0.477	−3.262	.235
5Y	−1.455	−2.456	.050	−0.732	−3.587	.248	−0.408	−0.544	−0.700	−2.994	.250
7Y	−1.619	−2.542	.048	−0.994	−3.481	.352	−0.164	−0.225	−0.981	−3.189	.351

This table contains results from regressing future excess returns on the log ratio of new orders to shipments of durable goods and the log ratio of construction starts to structures investment. Results from univariate and bivariate regressions are presented. Long horizon returns are overlapping sums of monthly returns following the forecast date. Values in parentheses are *t*-statistics computed from Hodrick's (1992) standard errors. Data are from 2/1958 to 12/2009.

Most of the same patterns are observed in bivariate regressions as well. At short horizons, *t*-statistics on NO/S are usually higher, while at long horizons Starts/SI tends to have higher *t*-statistics. In the cases in which NO/S was significant at long horizons in univariate regressions, including Starts/SI tends to subsume that significance. Similarly, the significance of Starts/SI is reduced at short horizons by including NO/S. The R-squares of the bivariate regression for long horizons are almost identical to those of the univariate regressions with Starts/SI.

Overall, it appears that NO/S reflects the shorter maturities in the term structure of risk premia, while Starts/SI better captures the longer maturities. This is consistent with the longer horizon of structures investment, which itself is the outcome of the much slower depreciation of structures relative to capital equipment.

4.6 Interpreting predictability

A conventional interpretation of the return predictability evidence is that NO/S captures time-varying risk premia. An alternative explanation that has been proposed in the literature is that it is mispricing rather than risk premia that drives investment behavior. Baker, Stein, and Wurgler (2003), for example, conclude that overpriced equity is a primary driver of corporate investment by potentially rational managers. Our results suggest an alternative story in which both investors and managers are biased in their tendency to overextrapolate past macroeconomic trends. Under this view, high NO/S is the result of firms chasing past economic growth by placing orders for new capital stock, anticipating that the positive trend will continue going forward. This results in a brief surge in investment as these orders are delivered, but few additional orders are placed once firms realize that their growth expectations have not materialized. Investors, whose forecasts of future demand were similarly overoptimistic, are also disappointed, causing stock prices to fall.

There are several reasons why the extrapolation story is inconsistent with our results. One is that high NO/S predicts low returns not only on stocks, but on bonds as well, in particular bonds issued by the U.S. Treasury. While stock returns could conceivably be low as the result of cash flow forecasts that are biased by overextrapolation, it is difficult to see why this would cause Treasury returns to be low at the same time.

The second reason is that it is only aggregate NO/S, and not industry-level NO/S, that has predictive power for future industry returns. Rhodes-Kropf, Robinson, and Viswanathan (2005), Hoberg and Phillips (2010), and Baker and Wurgler (2012) all argue that equity mispricing has a significant industry component, suggesting that investors and possibly managers have forecast biases that are common across firms in an industry. If the variation in NO/S reflects biased expectations rather than aggregate risk premia, then we would expect industry-level biases to be an important component of industry NO/S. Since the same biases will generate mispricing, we should find that an industry's NO/S will have a unique role in forecasting that industry's own returns. Instead, we find no evidence that industry-level NO/S has incremental predictive power relative to aggregate NO/S.

Finally, we argue that the relationship between NO/S and the prices of investment goods is inconsistent with an explanation based on overextrapolation by managers. If high NO/S indicates aggregate overinvestment, then a subsequent

Table 13
Predictability in investment goods prices

	Forecast horizon					
	1 quarter	2 quarters	1 year	2 years	3 years	5 years
			Raw prices			
Private fixed investment	0.070	0.141	0.245	0.446	0.596	0.826
	(2.815)	(2.772)	(2.085)	(1.919)	(2.256)	(2.734)
	0.092	*0.104*	*0.079*	*0.071*	*0.059*	*0.044*
Private equipment investment	0.057	0.127	0.289	0.625	0.889	1.116
	(2.178)	(2.284)	(2.362)	(2.614)	(3.481)	(3.289)
	0.054	*0.073*	*0.097*	*0.125*	*0.119*	*0.071*
Durable manufacturing goods	0.086	0.165	0.288	0.498	0.562	0.762
	(2.914)	(2.632)	(1.919)	(1.985)	(2.259)	(2.354)
	0.105	*0.107*	*0.089*	*0.078*	*0.047*	*0.033*
			Relative prices			
Private fixed investment	0.025	0.054	0.068	0.090	0.091	0.090
	(2.542)	(2.863)	(1.837)	(1.226)	(0.963)	(0.768)
	0.040	*0.072*	*0.033*	*0.016*	*0.006*	*0.000*
Private equipment investment	0.012	0.040	0.112	0.269	0.384	0.380
	(0.966)	(1.458)	(2.174)	(2.834)	(3.258)	(2.390)
	0.002	*0.020*	*0.053*	*0.106*	*0.116*	*0.047*
Durable manufacturing goods	0.041	0.078	0.111	0.142	0.057	0.026
	(2.265)	(2.287)	(1.546)	(1.408)	(0.633)	(0.207)
	0.051	*0.063*	*0.047*	*0.031*	*−0.002*	*−0.005*

This table reports results from univariate regressions of log price changes on lagged NO/S. The dependent variables in the top panel are changes in the log prices of private fixed investment, private equipment investment, and durable manufacturing goods. The dependent variables in the lower panel show log changes in the relative prices of the same goods, which are constructed by dividing each price level by the GDP deflator. For each set of values shown, the top number is the estimated slope coefficient, the middle number (in parentheses) is a t-statistic computed using the Newey-West method with the number of lags equal to the greater of two or 1.5 times the forecast horizon, and the number at the bottom (in italics) is an adjusted R-square. Intercepts are not reported. Data are quarterly from 1958Q2 to 2009Q4.

glut of investment goods should result in lower investment goods prices. We test this prediction by regressing future growth rates in investment goods prices, over horizons from one quarter to five years, on current ln NO/S. We examine the price levels for private fixed investment, private equipment investment, and durable manufacturing goods. We also look at these price series relative to the GDP deflator to see whether our results are driven by changes in investment goods specifically or overall inflation. Table 13 shows our regression results. For each regression we report the slope coefficient estimate, its Newey and West (1987) t-statistic, and the adjusted R-squared.[20]

Table 13 shows that high current NO/S unambiguously forecasts an increase in future investment goods prices. The coefficient on NO/S is always positive and is significant at most horizons for all three price series. The effect is similar when we measure the same prices relative to the GDP deflator. The fact that coefficients are lower in the relative price regressions shows that NO/S does

20 T-statistics computed using the method of Hodrick (1992) are higher because they do not account for autocorrelation in non-overlapping price changes.

forecast an overall rise in inflation, but since the coefficients remain positive and mostly significant this is not the full explanation. In short, we see no evidence that high NO/S creates a glut of investment goods.

While the evidence against overextrapolation is strong, it is nearly impossible to rule out that the predictability we document is due to irrational beliefs about economic fundamentals other than cash flows, which might drive misvaluation through a cost of capital channel. This is because prices formed under a biased probability assessment may be indistinguishable from those formed under rational beliefs with an alternative preference structure.

Our results on the term structure of risk premia imply, however, that such biases must have a very particular structure. The previous section suggested a relationship between the depreciation rate of an investment and the horizon of the excess returns that the particular investment forecasts. The risk premia interpretation implies that more slowly depreciating investments, given their longer economic lifetimes, will be sensitive to longer "maturity" discount rates and hence will forecast excess returns at longer horizons. For biased beliefs to generate these results, it should be the case that it takes longer for investors to recognize errors that affect their pricing of longer-term assets.

5. Conclusions

This paper has demonstrated a rich set of interrelations between the ratio of new orders to shipments of durable goods, the returns on stock and bond portfolios, and various measures of real output and investment. We introduce a new measure of investment commitments, new orders (NO) divided by shipments (S) of durable goods, and show that it has strong predictive ability over future returns on both stocks and bonds. The predictability is confirmed both in- and out-of-sample, and for most asset classes it is robust to the inclusion of other common predictors of returns. Our measure has strong predictive power for a number of macroeconomic variables as well.

Since durable goods spending represents physical capital investment by businesses and households, it should naturally reflect changes in discount rates and forecast future excess security returns with a negative sign. Consistent with this explanation, we find that high NO/S ratios tend to follow periods of prolonged consumption growth, which suggests that NO/S may capture the countercyclical risk premia endogenously generated by numerous asset pricing models.

While these relations are consistent with rational decision-making, several alternative hypotheses have been put forth in the behavioral literature that hold that investment might be influenced by mispricing rather than risk premia. We present several new results that are inconsistent with mispricing driven by overextrapolation of past economic trends. One is that NO/S forecasts returns on Treasury bonds, whose predictability is unlikely to be the result of biased cash flow forecasts. Another is that industry-level NO/S has no incremental power over aggregate NO/S in terms of predicting industry returns, which is contrary to what the mispricing hypothesis would imply. Finally, we find that high NO/S predicts rising investment goods prices, which is the opposite of what we would expect if high NO/S indicated overinvestment.

We also address the term structure of risk premia. Our main predictive variable, NO/S, best predicts returns to stocks and bonds at horizons up to one year, hence is primarily useful as a proxy for a shorter-term component in discount rates. The predictive horizon of NO/S is consistent with the relatively short lives of durable goods that the ratio covers, which are typically investments in equipment and inventories. The other major type of corporate investment is in structures, such as factory buildings and offices, which have much longer economic lives. Hence, investment commitments for structures should respond more to changes in longer-term risk premia. We confirm this intuition and find that an analogous ratio constructed from orders of nonresidential structures (Starts/SI) proxies for longer-term risk premia and predict asset returns at longer horizons. Hence, studying investment commitments for investments with different economic lifetimes allows us to understand the term structure of risk premia.

Our results contribute to an important debate in financial economics on the dynamics of investments and time-varying risk premia. The measure we introduce, the ratio of new orders to shipments, is unique in that it forecasts returns on corporate bonds, Treasury bonds, and the stock market. Our paper therefore complements a growing literature demonstrating that non-price-based macroeconomic variables can have significant predictive power over future asset returns.

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