New Orders and Asset Prices *

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Abstract

This paper investigates the behavior of the ratio of new orders to shipments of durable goods (NO/S). High levels of NO/S are associated with a business cycle peak. They predict a short-run increase in employment and fixed and inventory investment but a dramatic long-run decline in employment, fixed investment, inventories, and GDP as a whole. We also find that NO/S captures time-varying risk premia. Higher levels of NO/S forecast lower excess returns on a broad set of assets, including equities, long- and intermediate-term Treasury bonds, and high- and low-grade corporate bonds, at horizons from one month to one year. These effects are robust to the inclusion of all common return predictors. We then construct an equilibrium model of investment with time to plan and a countercyclical price of risk which implies that the ratio of new orders to shipments is procyclical and predicts lower excess returns.

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1 Introduction

New orders of durable goods are one of the most carefully tracked economic indicators. Released near the end of each month, the strength of new orders is used as a predictor of future manufacturing output and of macroeconomic conditions in general. The announcement is frequently cited in the financial press as the cause of major stock and bond market movements.[1]

The interest in this series, both relative to other economic indicators and also to the corresponding index of nondurable orders, is due to the fact that durable orders likely reflect a more forward looking assessment of the economy. This is true for several reasons. The first is that durable goods are largely comprised of capital spending and inputs to the production of other durables.[2] Thus, orders of durables should reflect the expectations of businesses about the future profitability of capital investment. Second, durable goods are different from most nondurables in that they often require a substantial amount of time to produce. An order for a durable consumption good, for instance, therefore reflects a view of future rather than current demand for that product. An order for durable capital equipment may reflect a view of consumer demand that is even more forward looking if the use of that equipment is in the future production of other durable goods.

One way to extract those longer term views is through the "book-to-bill ratio," used most commonly in the electronics industry. The Wall Street Journal, in its coverage of these announcements, describes this 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."[3] This interpretation of the ratio of new orders to shipments is natural. If new orders rise, then future shipments must rise at some horizon as long as there is not an increase in canceled orders or a permanent rise in unfilled orders.

The first goal of the current paper is to understand the behavior of the ratio of new orders to shipments (NO/S) and its relation to the business cycle. We find that NO/S peaks following periods of prolonged growth in output, particularly in consumption, and following decreasing unemployment and diminishing inventories. We also establish that aggregate NO/S has predictive ability over a number of important variables, but that these relations are far more complex than what would be suggested by its simple characterization as an indicator of a "good business outlook." As expected, higher NO/S does predict rising production, and the goods produced do raise nonresidential fixed investment and increase the stock of durable inventories.

[1] See, for example, "U.S. Stocks Fall Most Since July on Home Sales, Durable Goods," Elizabeth Stanton, Bloomberg, September 26, 2009.

[2] In March 2009, the breakdown of new orders was as follows: 10% were consumer durables, 33% were capital goods excluding defense, 6% were defense, 22% were construction materials, and 29% were intermediate goods to durable manufacturing.

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

However, all this occurs only at very short horizons of just 1-3 months. Following this initial surge we see rapidly falling investment and moderately lower consumption, with the overall effect being a decline in GDP at a horizon of 1-2 years.

Given the strength of these predictive relations, we then ask whether NO/S has predictive power for future stock and bonds returns as well. We find that higher NO/S is associated with lower stock and bond market returns over horizons from one month to one year. In particular, we find predictability in the excess returns of the value-weighted market portfolio, long- and intermediate-term Treasury bonds, and high- and low-grade corporate bonds. 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 (2008). This predictability is not just apparent in sample, but out of sample as well.

Since NO/S is constructed from the new orders and shipments of durable goods industries, we examine whether it has any ability to predict the spread between the returns on durable- and non-durable-producing industries. Gomes, Kogan, and Yogo (2009) find that the spread between durable and non-durable industries is positive on average, a result they attribute to the greater risk faced by durable producers. We find that the expected returns of durable producers are particularly high when NO/S is low, suggesting that the pricing of "durability risk" is at least partially captured by NO/S. We also examine whether it is aggregate NO/S or industry NO/S that better predicts future industry returns, and we find that industry NO/S has no explanatory power after controlling for aggregate NO/S. We interpret this result as evidence that aggregate NO/S is capturing a market-wide state variable rather than aggregating disparate sources of risk premia.

The observation that NO/S predicts returns to a variety of asset classes is notable. Even though the predictability of returns to different asset classes by a variety of predictors has been established in the literature, the set of variables that predict stock returns and the variables that predict bond returns are somewhat disjoint. NO/S contributes to the literature as a variable that predicts returns to several major asset classes, which suggests that NO/S captures a fundamental source of time-varying risk premia in the economy.

We investigate whether the relation between NO/S and future returns is obtained in a relatively stylized model of a production economy. In this model, we follow Berk, Green, and Naik (1999) and Zhang (2005) by assuming an exogenous pricing kernel that is countercyclical and driven by aggregate productivity shocks. In this model, firms maximize share value by optimizing their choice to pay out dividends or reinvest proceeds into additional capital goods, where firms face costs to adjust their capital stock. Critically, we modify this model by requiring that firms must plan investment and order new capital goods in advance, similar to Christiano and Todd (1996) and Porter (2005). This "new orders" series within the model provides an analog to the series we observe in reality.

After calibrating the model to match output and NO/S volatilities, we observe that NO/S is procyclical and negatively related to future asset returns. This is in contrast to the standard model without time to plan, which implies a countercyclical NO/S. The investment pattern generated by the model is also consistent with the empirical evidence that business investment lags output over the business cycle (e.g. Christiano and Todd, 1996) and the observation of a negative correlation between investment growth and stock returns (e.g. Lamont, 2000).

In the next section we introduce our data and describe the properties of NO/S. Results on the prediction of variables related to aggregate output are in Section 3, and return predictability results are in Section 4. We discuss some of these results in Section 5 and then present and solve our theoretical model in Section 6. We conclude in Section 7.

2 Data

The central focus of this paper is on the ratio of new orders of durable goods to shipments of durable goods. Both series 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 US 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 and the value of shipments of durable goods. Reported values for new orders are net of cancellations, which means that shipments and new orders obey the identity

$$\mathrm{NO}_{t+1} = \mathrm{S}_{t+1} + \mathrm{UO}_{t+1} - \mathrm{UO}_t,$$

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.

All M3 series are available in seasonally adjusted form, and we use these versions. All data from the survey is 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 we deflate these values using the PPI for durable manufactured goods. PPI data are not seasonally adjusted, so we seasonally adjusted them using the U.S. Census' X12a program.

In the M3 database, all data on durable goods are available monthly from February 1958 to the end of our sample in December 2008. Prior to 1992, industry classifications 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. We therefore use new orders and shipments data reported based on SIC codes until February 1992 and then extend the series by splicing on the NAICS-based growth rates starting in March 1992, the first date for which growth rates of all NAICS variables are available.

One 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 therefore 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.

For the ratio of new orders to shipments, the level of the SIC and NAICS series coincide at the beginning of 1992. In order to make our NO/S series as easy as possible to replicate, we simply use the SIC-based NO/S ratio up to February 1992 and the NAICS-based ratio (with the semiconductor adjustment) from March 1993 on. This series is almost identical, with a correlation coefficient of 0.998, to the series formed by taking the ratio of the new orders and shipments series that are extrapolated using the NAICS growth rates. All of our results are essentially identical regardless of the NO/S series used.

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 Phillips-Perron (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).

For comparison, the bottom panel of the figure 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.

Our variable is also 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. This annual series 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.[4] 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 investment goods, or other unknown factors.[5] Our series also differs substantially in that it is monthly and remains currently available.

Several other statistics presented in the table 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 suggested 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.

We augment these series with standard data items. Quarterly 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

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

[5] Whatever the reason is, 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.

[6] Here and throughout the paper all standard errors are computed using the method of Newey and West (1987) with the number of lags chosen automatically using the procedure of Newey and West (1994).

Reserve Board. Following Gomme, Kydland, and Rupert (2001), we construct a residential investment series by summing private residential fixed investment and durable consumption expenditures. The output gap measure of Cooper and Priestley (2008) 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 Ken French's web site. Long-term Treasury, corporate, and high yield bond returns are computed from Lehman Brothers indexes and backfilled with corresponding series from Ibbotson. Long-term Treasury, long-term corporate (Baa), and short-term 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 yields. The earnings yield is defined as the 4-quarter sum of S&P Composite earnings divided by the current index level.

3 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.

3.1 The dynamics of new orders and shipments

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 results of regressions in which quarter-end ln NO/S is regressed on past annualized growth rates of new orders and shipments. 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. 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 towards more typical values in 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.

$$\ln \mathrm{Y}_{t+\tau} - \ln \mathrm{Y}_{t+\tau-1} = \alpha + \beta \ \ln \mathrm{NO/S}_t + \epsilon_t, \tag{1}$$

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 the figure, 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 4 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.

Together, these results confirm what was before only suggested by visual evidence, namely that NO/S is strongly procyclical, highest following periods of economic growth. High levels of NO/S indicate an impending business cycle peak, as shipments growth is positively related to NO/S in the very short run but negatively related to NO/S at longer horizons.

3.2 Placing NO/S within the business cycle

To deepen our understanding of where NO/S fits within the business cycle, we next consider a much broader array of business cycle indicators. Table 3 contains the output from a number of regressions in which the dependent variable is again the log ratio of new orders to shipments, except now it is one quarter in the future. We now predict this value using a variety of growth rates in GDP, consumption, fixed investment, inventories, and unemployment, in addition to the term spread, the T-bill rate, the excess stock market return, and lagged ln NO/S. Growth rates and market returns are computed over four quarters.

Regression 1 captures two robust findings. One is that high NO/S follows periods of positive GDP growth. The other is that a high NO/S tends to follow a low term spread. Both these results confirm that NO/S is strongly pro-cyclical. We see no relation between NO/S and the T-bill yield. Regression 2 demonstrates that an additional lag of GDP growth does not add explanatory power. Past excess stock returns are insignificantly related to future NO/S, as demonstrated in regression 3. Lagged NO/S is marginally significant in regression 4, but including it as an additional explanatory variable has little effect on the other coefficients.

Regressions 5-7 suggest that GDP growth is not the business cycle measure that is most predictive of future NO/S. First, we see that growth in the unemployment rate subsumes all the explanatory power of GDP. Next, we see that the effect of GDP was mostly due to its consumption component, not investment. In regression 7, which reintroduces unemployment growth, we find that consumption growth remains significant.

Regression 8 adds past growth in inventories, which appears to have a significantly negative relation with future NO/S. This is consistent with the idea that new orders should naturally be expected to follow diminished inventories (to the extent that those inventories are at least partially made up of durable goods) as retailers must replenish their stocks of these goods. This last result turns out to be somewhat fragile, however. If we remove the one financial variable, the term spread, which was robustly significant, then the significance of inventory growth disappears. No other coefficient is substantially affected by the removal of the term spread, however.

3.3 Predicting economic activity with NO/S

We have shown that NO/S is positively and significantly related to future shipments of durable goods. We now seek to establish whether broader measures of economic output are similarly predictable, first using univariate analysis in which ln NO/S is the only predictor, and then with a number of control variables also included.

Evidence for predictability in GDP and a number of its components is presented in Figure 3. 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. We can see that the investment components are the primary drivers of the pattern we see in GDP. NO/S's positive short-run impact on GDP, itself not statistically significant, can be attributed to the brief surge in nonresidential fixed and inventory investment that follows high NO/S.

The initial surge in GDP following high NO/S is in spite of the decline in residential investment that is already taking place as NO/S is peaking. This observation is consistent with Gomme, Kydland, and Rupert (2001), who report that residential investment leads the business cycle by one quarter while nonresidential investment lags by one quarter. We note that the leading behavior of residential investment is roughly consistent with the behavior of new orders themselves. This suggests the absence of any lead time or "time to build" in residential investment, consistent with the assumptions of Gomme et al., which would follow if residential investment goods were produced to stock and not to order.[7]

In contrast, both nonresidential investment and shipments of manufacturing durables follow high NO/S with approximately a three month lag. The length of this surge of investment may not be far from the amount of time it takes for newly ordered durable goods to be shipped. 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.

[7] Gomme at al. estimates that it takes, one average, one quarter to complete residential investment and four quarters to complete nonresidential investment.

Given that orders for some types of goods will tend to be filled sooner and some later (for nondefense capital goods, the average ratio of unfilled orders to shipments is 6.85), it seems plausible that an investment surge lasting for several quarters may not be much longer than the time it takes for the orders that were already placed to ship. Thus, production lags may be very significant for the types of goods included in these categories.

Following the brief surge in nonresidential investment, GDP tends to decline for the next several years. This is again mostly an investment-led phenomenon, though some marginally significant declines in per capita consumption are also observed. The impact of NO/S disappears after about three years, as investment and consumption return to normal levels. Only inventory growth remains sensitive to NO/S at this long of a horizon.

Table 4 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 Wright (2006) and Ang, Piazzesi, and Wei (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 do not include the output gap measure in this regression for the simple reason that it is constructed from the full sample of industrial production data. By construction, the output gap will forecast future changes in industrial production, making the output gap's ability to predict future GDP growth also somewhat automatic.

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 4 demonstrate that the univariate significance of ln NO/S for longer horizon forecasts of GDP growth persists after controlling for the other variables. We continue to find no 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 of new orders. The growth of 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 a 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. In Table 5 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. These results reinforce the conclusion, drawn from Figure 2, that high NO/S foretells a business cycle peak, with predicted output growth that is higher in the very short run but lower for longer horizons.

These regressions also confirm earlier work that has consistently shown that steeper term structures predict higher GDP growth. We find some support for Ang, Piazzesi, and Wei's (2006) finding of a negative relation between the yield curve level and future GDP growth, but only for intermediate forecast horizons. In untabulated results, we also find that *cay* is also not related to future GDP growth after controlling for the other variables included in our regressions.

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

4 Return predictability

As a variable so intricately related to the business cycle, the ratio of new orders to shipments of durable goods might be expected to vary with expected rates of return for a number of reasons. The most obvious one may be that lower costs of capital should naturally be expected to increase new orders for durable investment goods. In this section we ask whether there is return predictability related to NO/S, whether it is robust to the inclusion of standard predictive variables, and for how long does it persist. We begin by running standard forecast regressions and then perform an out of sample forecast exercise to help gauge robustness.

4.1 In sample analysis

Most of the variables used in our predictive regressions are fairly standard. They consist of the earnings yield, the output gap measure of Cooper and Priestley (2008), and the most recent quarter-end value of Lettau and Ludvigson's (2001) *cay* variable, in addition to all the variables included in the previous GDP regressions. Returns are continuously compounded, and excess returns are constructed by subtracting off the continuously compounded riskless return. In all the return regressions, we follow Cooper and Priestley (2008) 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.[8]

Table 6 contains the correlation matrix of the variables in our predictive regressions. The correlations with 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 0.4 in absolute value, indicating that the information that NO/S provides is not redundant. Other variables, such as *cay* and the output gap or the T-bill and earnings yields, are significantly more highly correlated.

Table 7-A contains our results on forecasting the excess return on the U.S. stock market as proxied by the RMRF factor of Fama and French (1993). We report results for one-month, one-quarter, and one-year horizons. The table 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 (0.0345) decrease in ln NO/S raises the one-year expected excess return by 4.3%. R-squares from these univariate regressions range from 0.4% for monthly returns to 7.3% for annual returns. Little predictability is observed past the first year, so we do not report these results.

To some extent at the quarterly horizon but strongly at the annual horizon, the significance of NO/S is robust to the inclusion of a number of predictive variables, namely the earnings yield, *cay*, the term and default spreads, the Treasury bill rate, and the output gap measure of Cooper and Priestley (2008). 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 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 when additional controls are in place. The lack of robustness of the output gap as a return predictor seems

[8] Although the earnings yield is also observed with a lag, it is not common practice to allow extra lags to accommodate the reporting delay, and we follow this convention. Lagging this series by one or two more months has no material effect on our results.

surprising given the results of Cooper and Priestly (2008), but none of their regressions included *cay* as a control, as we do here. In untabulated results, we confirm Cooper and Priestly (2008) 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 restricted to stock returns. Table 7-B reports results for forecasts of excess returns on long-term Treasury bonds. The coefficients on ln NO/S are smaller here than they were for equities, though we now find some significance for the one-month regressions as well. Interestingly, controlling for other predictive variables has almost no effect on the coefficient on ln NO/S, and the R-squares are almost additive in that the sum of the R-squares of the two restricted regressions are close to the R-square of the unrestricted regression. Thus NO/S appears to capture a component of bond risk premia that is unrelated to the other predictors. Even stronger results are obtained when we examine intermediate-term Treasury returns, as shown in Table 7-C.

It is also notable that no variables other than ln NO/S are significant in both stock and Treasury bond regressions. The sole exception is the T-bill yield, which is barely significant at a one-year horizon in the long-term Treasury bond regressions and highly significant (albeit with the opposite sign) in the corresponding stock return regression. More commonly, variables that predict bond returns, like the term spread and the default spread, are not significant in the stock return regressions. Variables that predict stock returns, like *cay* and the earnings yield, show no ability to predict Treasury bond returns.

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 markets. Tables 7-D and 7-E repeat the return predictability regressions using investment-grade and high-yield corporate bonds. In both three cases, NO/S has significant forecast power at horizons from one month to one year, and the significance is usually robust to the inclusion of all of the control variables.

In other untabulated regressions, we obtain nearly identical results if we use the dividend yield in place of the earnings yield or the Cochrane and Piazzesi (2005) "tent" factor instead of the term premium. 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). While that variable often offered some improvement in in-sample return forecasts, including it had little effect on the other slope coefficient estimates, and specifically almost no effect on the slope coefficients estimated for NO/S.

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.

Because our regression-based forecasts might be sensitive to the forecast period, we vary our results by making our first forecast either 5, 10, or 20 years after the beginning of our sample. We refer to the amount of time prior to the first forecast as the "initialization period" in Table 8, which contains the results of the exercise.

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[9], or

$$\hat{R}_t \equiv \alpha_{t-1} + \beta_{t-1} \ln \frac{\mathrm{NO}_{t-1}}{\mathrm{S}_{t-1}}.$$

The coefficients α_{t-1} and β_{t-1} are estimated using returns up to period $t-1$.

The "R-squared" measure used by Campbell and Thompson (2005) 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 (2005), 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.

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.

[9] 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.

4.3 Is it new orders or is it shipments?

The ln NO/S series shows a strong ability to forecast future returns, but is the effect driven mostly by the numerator or the denominator, or are both equally important? Of course, without any adjustment, neither NO or S is likely to be much use by themselves. The reason is that these series are highly nonstationary, with a large trend component, making them unsuitable as explanatory variables in any predictive regression. By examining their ratio, we have eliminated this trend.

In this section we pursue an alternative detrending procedure that will allow us to examine NO and S separately. Obviously, for any series T we have

$$\ln \mathrm{NO/S}_t = (\ln \mathrm{NO}_t - \mathrm{T}_t) - (\ln \mathrm{S}_t - \mathrm{T}_t)\,.$$

If both $\ln \mathrm{NO} - \ln \mathrm{T}$ and $\ln \mathrm{S} - \ln \mathrm{T}$ were stationary, then either one might be useful as a predictor. A regression that included both would clearly nest the specification that includes only ln NO/S.

The fact that we can reject a unit root for ln NO/S implies that ln NO and ln S share a common trend. We estimate this trend by applying a one-sided Hodrick-Prescott (1997) filter to the average of ln NO and ln S. The one-sided filter involves re-running the HP filter for progressively larger sample sizes, so that only data through time t are used to estimate T_t. We use the one-sided filter so that our detrended predictors do not inherit spurious predictive ability from a dependence on future data. For the bandwidth parameter we follow Ravn and Uhlig (2002) and choose a value of 129,600. Finally, we discard the first two years of detrended data so that the trend is estimated from at least two years of data.

We define the resulting detrended new orders and shipments data as $\ln \mathrm{NO}_t^* = \ln \mathrm{NO}_t - \mathrm{T}_t$ and $\ln \mathrm{S}_t^* = \ln \mathrm{S}_t - \mathrm{T}_t$. Using ADF and Phillips-Perron tests, we can reject a unit root in both series at all conventional significance levels. In Table 9, we include one or both of these variables separately in quarterly return forecast regressions. We compare these to a univariate regression in which ln NO/S is the sole predictor. (Univariate regression results differ slightly from earlier ones due to the fact we are dropping the first two years of the sample.) To conserve space, we only report quarterly return regressions for three assets: equity, long-term Treasury bonds, and high-grade corporate bonds. Results for intermediate-term Treasuries and high-yield corporates are similar.

The table first shows that stock returns are driven more by new orders than by shipments. By themselves, $\ln \mathrm{NO}_t^*$ is statistically significant but $\ln \mathrm{S}_t^*$ is not. Together, both variables are significant, with coefficients similar in magnitude but opposite in sign, resulting in a fit that is almost identical to the univariate regression with ln NO/S. For both bond series, neither $\ln \mathrm{NO}_t^*$ nor $\ln \mathrm{S}_t^*$ is significant without the other, suggesting that it is the interaction of new orders and shipments, not one series or the other, that is most useful in forecasting returns. The last column of the table includes the p-value of a t-test of the equality of the coefficients on $\ln \mathrm{NO}_t^*$ and $\ln \mathrm{S}_t^*$. In all three cases we fail to reject equality, suggesting that our formulation of ln NO/S is reasonably well specified.

4.4 Industry returns

Since NO/S is constructed from the new orders and shipments of only durable goods industries, it might be expected to predict returns on these industries with greater accuracy. In this section we examine whether or not this is the case by separately examining returns on durable manufacturing, non-durable manufacturing, and non-manufacturing sectors.

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, durable returns are higher when durable expenditures are low relative to the stock of durable goods. They interpret these result 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.

Following the system used by the Census' 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. Non-manufacturing consists of SIC codes between 01 and 17 and between 40 and 89. Non-manufacturing industries are mostly services but notably also include agriculture, mining, and oil. Unlike Gomes, Kogan, and Yogo (2009), we do not distinguish firms that produce consumer products from those that produce investment goods or who primarily provide goods or services for government or export. Based on these classifications, we compute the returns on three value-weighted portfolios from the industry returns data provided by Ken French.

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

The table shows that NO/S, like Gomes, Kogan, and Yogo's durable expenditure-stock ratio, predicts durable goods industries most 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. Returns on the non-manufacturing sector respond in a way that is similar to durables. This conflicts somewhat with the Gomes, Kogan, and Yogo interpretation of durable-related predictability since non-manufacturing returns are substantially less volatile than durable returns, the former having an annualized standard deviation of around 15% and the latter having a 20% volatility.

A second use of industry data is in examining whether it is aggregate NO/S or industry-level NO/S that is a better predictor of industry returns. If aggregate NO/S is a proxy for some market-wide state variable, then industry-level NO/S should offer little incremental explanatory power for industry returns. If industry-level NO/S is also useful in predicting industry returns, then perhaps it is better to think about aggregate NO/S as representing a combination of disparate sources of risk premia.

Until March of 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, 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 Ken 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.

We believe these results are useful in understanding the mechanism driving the relation between NO/S and returns. Some predictive variables, like the T-Bill yield, appear to reflect pure time variation in aggregate risk-premia. The earnings-price ratio, in comparison, seems more likely to reflect many different sources of risk premia, as evidenced by the fact that firms with high E/P ratios do relatively well even at times when aggregate E/P is low. Results from the panel regressions suggest that NO/S belongs to the former category, a proxy for some systematic risk premium and not an amalgamation of premia arising from unrelated origins.

5 Discussion

The results in the previous two sections have uncovered a number of new links between the macroeconomy and expected asset returns. One interpretation is that high NO/S results from the low costs of capital we observe following sustained periods of consumption growth and declining unemployment. In the external habit model of Campbell and Cochrane (1999), for instance, prolonged consumption growth is associated with high values of 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.

Following Abel and Blanchard (1986), a lower cost of capital can create a significant incentive to increase the capital stock. This is manifested in the ratio of new orders of durable goods to shipments because durable goods are predominantly investment goods of one form or another, of which capital goods are one type. Other forms of durable goods, like consumer durables, can also be considered a form of investment, as argued by Eberly (2002). Thus, when NO/S is high, it is almost unavoidable that there is a short-run rise in the growth rate of investment, the effect that Lettau and Ludvigson (2002) argue can sometimes be obscured by adjustment or delivery lags in the investment process. Lettau and Ludvigson demonstrate an additional implication of Q theory, namely a positive long-run relation between investment growth and the cost of capital, which they argue is robust to such frictions.

The patterns in investment growth observed in Figure 3 are generally consistent with these predictions. High NO/S, which we have demonstrated is consistent with a low cost of capital, predicts an initial rise in nonresidential fixed investment and private durable inventories, though not in residential investment. At longer horizons, the relationship becomes negative, as Lettau and Ludvigson would predict.

Although we interpret the new orders and shipments series we use as measures of new orders and shipments of investment goods, arguably purer measures might be given by the new orders and shipments of total capital goods, nondefense capital goods, or even nondefense capital goods excluding aircraft, all subsets of the series we use. We have examined the NO/S ratio constructed from all these series and find very similar results in predicting economic activity and asset returns.

Another related variable is the PMI Composite Index from the Institute for Supply Management. The PMI Index is a composite (an equal weighted average as of January 2001) of five diffusion indexes based on the results of qualitative surveys to purchasing managers. Managers are asked whether their business is improving or worsening in five different areas, namely new orders, inventories, employment, production, and deliveries.

The correlation of the PMI Index with ln NO/S is 0.50. It is not as highly procyclical as NO/S, with a correlation of 0.30 with the HP-detrended level of real GDP (as opposed to 0.49 for ln NO/S). As demonstrated by Dasgupta and Lahiri (1993) and others, the PMI Index predicts short-run GDP growth with a positive sign, and for this purpose it is a stronger predictor than NO/S. However, it does not capture the longer-run (3-8 quarters) decline in output and investment that a high level of NO/S implies and that we believe to be our more interesting finding.

The PMI Index does a reasonable job of predicting stock returns. In univariate regressions, the index does not predict bond returns with much reliability. Its predictive power increases when additional controls are in place, and it is often significant in multivariate regressions. Because it tends to work better with other controls in place, its performance in the kind of out-of-sample predictions examined in Table 8 is generally poor.

6 Theoretical model

Our goal in building a model is to investigate the theoretical behavior of NO/S over the business cycle and its relationship to asset returns. In Section 3 we document that NO/S is procyclical. Section 4 documents that NO/S predicts lower excess returns to a broad set of assets, including stocks and several types of corporate and government bonds.

We construct an equilibrium model in which a representative producer faces aggregate uncertainty. The firm is endowed with a Cobb-Douglas production technology and faces adjustment costs when modifying its fixed capital. Similar to Christiano and Todd (1996) and Porter (2005), the model incorporates time to plan, in that firms must plan investments and order investment goods one period before those investments begin affecting production. We interpret planned investment as new orders of investment goods, and actual investment as shipments of investment goods. We take the process describing the pricing kernel to be exogenous.

6.1 Firm and Technology

The representative firm uses physical capital and labor to produce a homogeneous good with a constant returns to scale production technology given by

$$\begin{aligned} Y_t &= F(A_t, K_t, L_t) \\ &= (A_t L_t)^{1-\theta} K_t^{\theta} \end{aligned}$$

where Y_t denotes output, K_t the firm's fixed capital stock, L_t the number of hours worked by labor, and $a_t = \log(A_t)$ denotes aggregate productivity. Below we will simplify the model by assuming that labor is supplied inelastically, normalized to $L_t = 1$.

We model log productivity with the unit root process

$$a_{t+1} = a_t + \varepsilon_{t+1}^a \tag{2}$$

where $\varepsilon_{t+1}^a \sim$ i.i.d. $\mathrm{N}\left(0, \sigma_a^2\right)$. This implies that productivity shocks are permanent, an assumption that has been made at least as far back as Prescott (1986). More recently, permanent shocks have been shown by Croce (2005) and Backus, Routledge, and Zin (2007) to offer advantages in matching asset prices, though Kaltenbrunner and Lochstoer (2008) argue that the unit root assumption has drawbacks as well as benefits.

The capital accumulation rule is

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

where I_t denotes investment. The investment is subject to quadratic adjustment costs, g_t, which are given by

$$g(I_t, K_t) = \frac{1}{2}\xi \frac{(I_t - \delta K_t)^2}{K_t}$$

Adjustment costs are therefore paid when net investment, or gross investment minus depreciation, are nonzero. The costs are quadratic in net investment, with a magnitude that is determined by the parameter ξ.

Crucial to our model is the assumption that investment is planned one period ahead of time. At time t, the firm plans investment at time $t+1$ and invests what it planned to invest at time $t-1$. Therefore, time $t+1$ investment becomes a time t choice variable. We assume that these decisions are irreversible – once a firm commits to new capital investment it cannot alter that commitment.[10]

The firm is equity financed. The dividend to shareholders is equal to

$$D_t = Y_t - [I_t + g_t] - w_t L_t, \tag{4}$$

where w_t is the wage payment to labor services. Labor markets are competitive, so wage payments are determined by the marginal product of labor.

At each date t, the firm chooses $\{I_{t+1}\}$ to maximize the net present value of their expected dividend stream,

$$\mathrm{E}_t \left[\sum_{k=0}^{\infty} M_{t,t+k} D_{t+k} \right], \tag{5}$$

[10] Were investment a sufficiently large fraction of output, it could be conceivable that the investment commitment could exceed total output. In practice, investment is too low and productivity shocks too small for this to occur with any nontrivial probability.

subject to Eqs. (2) and (3), where $M_{t,t+k}$ is the stochastic discount factor between time t and $t+k$.

The pricing equations that come out of the firm's optimization problem are:

$$1 = \int M_{t+1} R^I_{t+1} p_a(a_{t+1}|a_t) d_a \tag{6}$$

where $p_a(a_{t+1}|a_t)$ is the transition density of a_t defined by (2) and where

$$R^I_{t+1} = \frac{(1-\delta)\, q_{t+1} + \mathrm{E}_t M_{t+1,t+2}\left(\theta A^{1-\theta}_{t+2} K^{\theta-1}_{t+2} L^{1-\theta}_{t+2} - \frac{1}{2}\xi\left[\delta^2 - \frac{I^2_{t+2}}{K^2_{t+2}}\right]\right)}{q_t}$$

and

$$q_t = \left(1 + \xi \frac{I_{t+1} - \delta K_{t+1}}{K_{t+1}}\right) \mathrm{E}_t M_{t+1}.$$

q_t is Tobin's q, the consumption good value of a newly planned capital investment.

Multiplying both sides of Eq. (6) by K_{t+2}, rearranging, and adding $\mathrm{E}_t M_{t+1} D_{t+1}$ to both sides of the equation leads to:

$$\begin{aligned} & q_t K_{t+2} + \mathrm{E}_t M_{t+1} D_{t+1} \\ & = \int M_{t+1}\left(q_{t+1} K_{t+3} + \mathrm{E}_{t+1} M_{t+1,t+2} D_{t+2} + D_{t+1}\right) p_a(a_{t+1}|a_t) d_a. \end{aligned} \tag{7}$$

The ex-dividend value of a firm's equity (V_t) is equal to:

$$V_t = q_t K_{t+2} + \mathrm{E}_t M_{t+1} D_{t+1}. \tag{8}$$

Replacing equations (8) and (4) in (7) gives the standard Euler equation:

$$1 = \int M_{t+1} \frac{V_{t+1} + D_{t+1}}{V_t} p_a(a_{t+1}|a_t) d_a. \tag{9}$$

6.2 The Stochastic Discount Factor

Following Berk, Green and Naik (1999) and Zhang (2005), we directly parameterize the pricing kernel without explicitly modeling the consumer's problem. We adopt a variation of the pricing kernel specification in Zhang (2005):

$$\begin{aligned} \log M_{t+1} &= \log\beta - \gamma_t\left(a_{t+1} - a_t\right) - \frac{1}{2}\gamma_t^2 \sigma_a^2 \\ \log\gamma_t &= \gamma_0 + \gamma_1 x_t \\ x_t &= \rho_x x_{t-1} + \left(a_{t+1} - a_t\right) \end{aligned} \tag{10}$$

where β, $\gamma_0 > 0$, $\gamma_1 < 0$, and $0 \leq \rho_x \leq 1$ are constant parameters.

Our model shares a number of similarities with Zhang (2005).[11] M_{t+1}, the stochastic discount factor from time t to $t+1$, is driven by $a_{t+1} - a_t$, which in our model is equal to the shock to the productivity process in period $t+1$. The volatility of M_{t+1} is time-varying, driven by the γ_t process. As in Zhang, this volatility takes higher values following business cycle contractions and lower values following expansions, implying a countercyclical price of risk as the result. In Zhang's model, countercyclical volatility was ensured by writing γ_t as a decreasing function of log productivity a_t. In our model, the nonstationarity of a_t necessitates an alternative approach. We therefore define the process x_t as an exponential moving average of past productivity shocks, which is stationary as long as $|\rho_x| < 1$, and write γ_t as a decreasing function of x_t.[12]

Two other differences with Zhang (2005) are worth noting. One is the inclusion of the term $-\frac{1}{2}\gamma_t^2\sigma_a^2$ in the pricing kernel. This term ensures that the pricing kernel has a constant expectation and implies that the riskless rate is equal to $-\log\beta$ in every period. The second difference is the exponential rather than linear specification of γ_t. The exponential guarantees positivity of γ_t, which prevents the relationship between M_{t+1} and $a_{t+1} - a_t$ from becoming perversely positive for high values of x_t.

6.3 Calibration and Quantitative Results

Solving our model generates equilibrium solutions for macroeconomic aggregates such as output, orders of investment goods (investment plans), and actual investment (shipments of investment goods). We are interested in investigating whether the cyclical behavior of NO/S and the observed relation between NO/S and future returns are obtained in the model.

Table 12 reports the key asset return moments and macro volatilities from the data that are matched by our calibrated economies. These include the unconditional Sharpe ratio, the average risk free rate, the average excess stock return, and the volatilities of output growth and NO/S.

We calibrate the model at a quarterly frequency, which implies a one-quarter investment planning horizon. This planning horizon is consistent with our rough empirical estimate, which we obtained by dividing unfilled orders of durable goods by shipments of durable goods. Following Kydland and Prescott (1982), the capital

[11] Zhang (2005) motivates a similar pricing kernel as a reduced-form representation of the intertemporal marginal rate of substitution for a fictitious representative consumer with power utility and relative risk aversion coefficient γ. The log pricing kernel for the representative agent economy is $\log M_{t+1} = \log\beta + \gamma(c_t - c_{t+1})$, where c_t denotes log aggregate consumption. c_t can be linked to the aggregate state variable, productivity, in a reduced form way by letting $c_t = \alpha_0 + \alpha_1 a_t$, where $\alpha_1 > 0$. Equation 10, except for the last term, now follows immediately by defining γ_t to be $\gamma\alpha_1$.

[12] 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 Barberis, Shleifer and Vishny (1998) from time varying investor sentiment; in Guvenen (2008) from limited participation; in Bansal and Yaron (2004) from time varying economic uncertainty and in Piazzesi, Schneider and Tuzel (2007) from time varying consumption composition risk.

share θ is set to 0.36, and the quarterly depreciation rate for fixed capital, δ, is set to 2.5% percent. We set the conditional volatility of the productivity process, σ_a, to 1.5%, which is sufficient to replicate the 1% quarterly output growth volatility observed in the data. The adjustment cost parameter, ξ, takes on different values, but they are always chosen to match the 3.5% quarterly volatility we observe in ln NO/S.

The parameters of the pricing kernel are picked to match the aggregate return moments computed by Storesletten, Telmer, and Yaron (2007). The time discount factor, β is set to 0.997 to produce a low real risk free return in the data, about 1.3% annually. γ_0 determines the unconditional price of risk, and it is set to 2.6 to match the annual Sharpe ratio of 0.41 observed in the data. γ_1 determines the degree of time variation in the price of risk. $\gamma_1 = 0$ implies a constant price of risk, and $\gamma_1 < 0$ implies countercyclical price of risk. We will consider several different values of γ_1, but all will be chosen such that the model matches the average equity premium of 6.8%.

The last parameter to be specified is ρ_x, the autocorrelation of the state variable driving risk premia. The data offer little guidance on how to select this parameter, so we consider values of 0.7, 0.8, and 0.9. In order to match the equity premium, each value of ρ requires different values of γ_1 and ξ. These values are reported in Table 13.

There are many similarities among the three model economies that we compute. In all cases, the calibrated model generates procyclical NO/S: The correlation between NO/S and the contemporaneous productivity shock (as well as output growth) is always around 0.90. The correlation between NO/S and the state variable x_t is between 0.3 and 0.4, and NO/S's correlation with the price of risk ranges between -0.3 and -0.4.[13]

These results are quite different from what a standard model without time to plan would imply. In a more standard model, in which expected investment (next period) is the most natural proxy for new orders, NO/S is countercyclical: In periods of high productivity growth, high contemporaneous investment (i.e. shipments) causes an immediate rise in the capital stock. Given this ability to adjust capital without a delay, the effect on next period's expected investment (i.e. new orders) is comparatively small. The result is a slight drop in NO/S. The standard model would also imply a high contemporaneous correlation between investment and output, which is in contrast to the empirical observation that business investment lags output over the business cycle (Christiano and Todd, 1996; Gomme, Kydland and Rupert, 2001).

In contrast, the model with time to plan generates a procyclical NO/S: When the economy experiences a positive productivity shock, the firm increases its orders for investment goods relative to its current investments, which were planned in the previous period. Whenever the realized productivity exceeds expected

[13] The procyclicality of NO/S is not sensitive to the assumption of a time varying price of risk, and we obtain the same result even with a constant Sharpe ratio. However, in the absence of time variation in the price of risk, excess returns are not countercyclical. Hence, we need a time varying price of risk to link NO/S to excess returns.

productivity, new investment plans exceed current investments. This leads to both procyclical NO/S and a lag between investment and output over the cycle.

Figure 4 plots the impulse response functions of output, new orders (investment plans), shipments (actual investment), NO/S, the price of risk, and the expected excess return following a one percent productivity shock, both for the standard model and the model with time to plan. Real variables (output, shipments, and new orders) are normalized to have a unit quantity at time zero, where the shock occurs at time one. Time zero values of NO/S, the price of risk, and the risk premium are steady state values.

For both models, output, new orders (or planned investment in the standard model), and risk premia respond almost identically to the shock. In the model with time to plan, however, shipments respond with a lag. The result is that NO/S immediately jumps up following the rise in productivity. In contrast, for the standard model there is a slight dip in NO/S as the impact on investment goods that are to be shipped immediately exceeds the impact on planned investment to be shipped later.

We then gauge whether the model can generate the return predictability observed in the data by running regressions on simulated model data in which we forecast excess stock returns with lagged ln NO/S:

$$r_{t+1}^{e} = \alpha_0 + \alpha_1 \ln \mathrm{NO/S}_t + \epsilon_{t+1}$$

The results, for the three sets of parameter values we consider, are reported in Table 13. In all cases, NO/S predicts excess stock returns with a negative coefficient, but the R-squares are much higher for lower values of ρ_x. In particular, when we calibrate the model with $\rho_x = 0.7$, we match the 3.3% R-square found in the data and reported in Table 7-A, though the largest slope coefficient found in the simulations, -0.31, is somewhat smaller than the -0.435 value estimated from actual data. We conclude that our model is capable of matching a number of qualitative features of the data, but that additional work would be useful in validating our choice of ρ_x.

Finally, in our model it is possible to measure how much the countercyclical risk premia that are required to match excess stock returns affect firm investment decisions. We do so by setting to zero the parameter γ_1, which determines the relationship between pricing kernel volatility and the state variable x_t. Impulse response functions under the original model, with time to plan, and the identical model with constant risk premia are plotted in Figure 5. The figure shows that the immediate rise in investment following a positive productivity shock is more than doubled by the presence of time-varying risk premia. Only after about ten quarters following the shock do the models with and without time-varying risk premia converge. Furthermore, the model without countercyclical risk premia only produces a 1% volatility of NO/S, while our benchmark model is calibrated to match the data with a volatility of 3.5%. Time variation in risk premia therefore generates about 90% of the variance of investment growth.

7 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. Our first main result is that NO/S has a significant ability to forecast excess returns on stocks and a variety of bonds at horizons from one month to one year, both in and out of sample.

Our paper complements a recent strand of the literature that has demonstrated that non-price-based macroeconomic variables can have significant predictive power for future asset returns. One such paper, described above, is by Cooper and Priestley (2008), who demonstrate that returns can be predicted by a measure of the output gap. Another is Piazzesi and Swanson (2008), who find that returns to Federal funds can be predicted with the unemployment rate. A final example is Piazzesi, Schneider, and Tuzel (2007), who find that the expenditure share of housing predicts stock returns. What is notable about our new variable, the ratio of new orders to shipments, is that it is the only one of these macro-based variables that has been shown to forecast corporate bond, Treasury bond, and stock market returns.

We find that high NO/S ratios tend to follow periods of prolonged economic expansion, suggesting that NO/S may capture the countercyclical risk premia endogenously generated by numerous asset pricing models of endowment economies. We then examine whether the low costs of capital implied by high levels of NO/S are consistent with aggregate patterns of investment behavior. Standard Q theory implies that high NO/S (indicating low costs of capital) should lead to a short-lived increase in investment. The long-run implications of Q theory, as stated by Lettau and Ludvigson (2002), are the exact opposite, with high NO/S leading to lower long-run growth rates in investment. Our findings are generally supportive of both hypotheses.

Together, these observations place NO/S at the intersection of a number of different channels at work in the real economy and in asset markets. We believe that additional work that focuses on each channel might result in substantial new insights.

A Appendix: The Firm's Problem, the Return to Investment Plan, and Stock Returns

The firm maximizes firm value. Let $M_{t,t+i}$ denote the stochastic discount factor from time t to time $t+i$. The firm's problem is then:

$$\max_{\{I_{t+i+1},K_{t+i+2},L_{t+i}\}} \mathrm{E}_t \left[\sum_{i=0}^{\infty} M_{t,t+i} \left\{ \begin{array}{c} A_{t+i}^{1-\theta} K_{t+i}^{\theta} L_{t+i}^{1-\theta} - w_{t+i} L_{t+i} - I_{t+i} - \frac{1}{2}\xi \frac{(I_{t+i}-\delta K_{t+i})^2}{K_{t+i}} \\ -q_{t+i}\left(K_{t+i+2} - (1-\delta) K_{t+i+1} - I_{t+i+1}\right) \end{array} \right\} \right]$$

where q_t denotes the shadow price of the capital accumulation constraint, Tobin's q. The first order condition with respect to labor, L_t delivers wages:

$$w_t = (1-\theta) A_t^{1-\theta} K_t^{\theta} L_t^{-\theta}.$$

Each period in time t the firm plans how much to invest in the following period, $t+1$, taking prices (w and q) as given. The first order conditions with respect to I_{t+1} and K_{t+2} delivers the Euler equation:

$$\begin{aligned}
0 &= q_t + \mathrm{E}_t M_{t+1} \left(-1 - \xi \frac{I_{t+1} - \delta K_{t+1}}{K_{t+1}} \right) \\
q_t &= \left(1 + \xi \frac{I_{t+1} - \delta K_{t+1}}{K_{t+1}} \right) \mathrm{E}_t M_{t+1} \qquad (11) \\
0 &= -q_t + (1-\delta)\, \mathrm{E}_t M_{t,t+1} q_{t+1} + \mathrm{E}_t M_{t,t+2} \left(\theta A_{t+2}^{1-\theta} K_{t+2}^{\theta-1} L_{t+2}^{1-\theta} - \frac{1}{2}\xi \left[\delta^2 - \frac{I_{t+2}^2}{K_{t+2}^2} \right] \right) \\
1 &= \frac{(1-\delta)\, \mathrm{E}_t M_{t,t+1} q_{t+1} + \mathrm{E}_t M_{t,t+2} \left(\theta A_{t+2}^{1-\theta} K_{t+2}^{\theta-1} L_{t+2}^{1-\theta} - \frac{1}{2}\xi \left[\delta^2 - \frac{I_{t+2}^2}{K_{t+2}^2} \right] \right)}{q_t} \\
1 &= \mathrm{E}_t \left(M_{t,t+1} \frac{(1-\delta)\, q_{t+1} + \mathrm{E}_t M_{t+1,t+2} \left(\theta A_{t+2}^{1-\theta} K_{t+2}^{\theta-1} L_{t+2}^{1-\theta} - \frac{1}{2}\xi \left[\delta^2 - \frac{I_{t+2}^2}{K_{t+2}^2} \right] \right)}{q_t} \right) \qquad (12)
\end{aligned}$$

Equation 12 is the familiar law of one price. The firm's investment return is:

$$R_{t,t+1}^{I} = \frac{(1-\delta)\, q_{t+1} + \mathrm{E}_t M_{t+1,t+2} \left(\theta A_{t+2}^{1-\theta} K_{t+2}^{\theta-1} L_{t+2}^{1-\theta} - \frac{1}{2}\xi \left[\delta^2 - \frac{I_{t+2}^2}{K_{t+2}^2} \right] \right)}{q_t}$$

Specifically, $R_{t,t+1}^{I}$ is the investment return from planning at time t to make an additional unit of investment at time $t+1$. The investment strategy can be undertaken at time t by making an investment plan to invest I_{t+1} at time $t+1$ and investing an appropriate amount in risk free asset such that the proceeds will exactly cover the investment plan when it is due.

In this setup, due to one period lag between investment plans and actual investments, the firm return is not the same as the return to new investment plans. Investment return from period t to $t+1$ concerns the tradeoff between marginal benefits and marginal costs of new investment plans initiated at period t. But the stock return is the return to the entire firm that includes not only the new investment plans, but also the already installed capital. The ex-dividend firm value and dividend level are:

$$
\begin{aligned}
P_t &= q_t K_{t+2} + \mathrm{E}_t M_{t+1} D_{t+1} \\
D_{t+1} &= \theta A_{t+1}^{1-\theta} K_{t+1}^{\theta} L_{t+1}^{1-\theta} - I_{t+1} - \frac{1}{2}\xi \frac{\left(I_{t+1} - \delta K_{t+1}\right)^2}{K_{t+1}}
\end{aligned}
$$

The firm value reflects the present value of next period's installed capital (which includes new planned investment) and the present value of expected dividends next year. The stock return is defined as:

$$
R_{t,t+1}^S = \frac{P_{t+1} + D_{t+1}}{P_t}.
$$

Since then the process for productivity is non-stationary, we need to normalize the economy by A_t in order to be able to numerically solve the model. We define $\widehat{C}_t = C_t/A_t$, $\widehat{K}_t = K_t/A_{t-2}$, $\widehat{I}_t = I_t/A_{t-1}$, $\widehat{P}_t = P_t/A_t$, $\widehat{D}_t = D_t/A_t$ and substitute. In the transformed model all variables are stationary. We solve the normalized set of equations and then re-scale the variables after having solved the model. The equations of the normalized economy are:

$$
\begin{aligned}
\widehat{K}_{t+1} &= e^{-g-\varepsilon_{t-1}}(1-\delta)\widehat{K}_t + \widehat{I}_t \\
1 &= E_t\left(M_{t,t+1} R_{t,t+1}^I\right) \\
R_{t,t+1}^I &= \frac{(1-\delta)\, q_{t+1} + E_{t+1} M_{t+1,t+2}\left(\theta e^{(1-\theta)(2g+\varepsilon_{t+1}+\varepsilon_{t+2})} \widehat{K}_{t+2}^{\theta-1} L_{t+2}^{1-\theta} - \frac{1}{2}\xi\left[\delta^2 - \frac{\widehat{I}_{t+2}^2 e^{2g+2\varepsilon_{t+1}}}{\widehat{K}_{t+2}^2}\right]\right)}{q_t} \\
q_t &= \left(1 + \xi \frac{\widehat{I}_{t+1} e^{g+\varepsilon_t} - \delta \widehat{K}_{t+1}}{\widehat{K}_{t+1}}\right) E_t M_{t+1} \\
R_{t,t+1}^S &= e^{g+\varepsilon_{t+1}} \frac{\widehat{P}_{t+1} + \widehat{D}_{t+1}}{\widehat{P}_t} \\
\widehat{P}_t &= q_t \widehat{K}_{t+2} + E_t M_{t+1} \widehat{D}_{t+1} e^{g+\varepsilon_{t+1}} \\
\widehat{D}_{t+1} &= \theta e^{-\theta(2g+\varepsilon_t+\varepsilon_{t+1})} \widehat{K}_{t+1}^{\theta} L_{t+1}^{1-\theta} - \widehat{I}_{t+1} e^{-g-\varepsilon_{t+1}} - \frac{1}{2} e^{-2g-\varepsilon_t-\varepsilon_{t+1}} \xi \frac{\left(\widehat{I}_{t+1} e^{g+\varepsilon_t} - \delta \widehat{K}_{t+1}\right)^2}{\widehat{K}_{t+1}}
\end{aligned}
$$

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Table 1: NO/S summary statistics

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 12/2008. 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.

	Levels:	First differences		
	ln NO/S	ln NO/S	ln NO	ln S
Full sample mean	0.0148	0.0001	0.0019	0.0018
NBER expansion mean	0.0172	0.0003	0.0046	0.0043
NBER recession mean	0.0009	-0.0015	-0.0138	-0.0123
t-statistic of difference	-1.6030	-0.5647	-4.4558	-7.6183
Full sample standard deviation	0.0345	0.0287	0.0359	0.0213
NBER expansion standard deviation	0.0321	0.0287	0.0352	0.0208
NBER recession standard deviation	0.0438	0.0291	0.0363	0.0187
t-statistic of difference	0.8675	0.1209	1.0468	0.5155
1st order autocorrelation	0.6593	-0.3796	-0.2798	-0.1208
12th order autocorrelation	0.1400	-0.0328	-0.0277	-0.1288
Augmented Dickey-Fuller statistic	-14.0023	-36.0801	-32.1582	-28.3334
Phillips-Perron statistic	-30.4386	-44.0370	-37.4188	-19.9703

Table 2: The determinants of NO/S

This table displays regressions in which the dependent variable is the end-of-quarter value of $\ln \mathrm{NO}/\mathrm{S}_t$, where NO and S denote new orders and shipments, respectively, of durable goods. Explanatory variables are three lags of annual growth rates in new orders (NO) and shipments (S). All data are real and seasonally adjusted, and the sample is from 1958Q2 to 2008Q4. Newey-West t-statistics in parentheses use 6 lags.

Intercept	$\Delta \ln \mathrm{NO}_t$	$\Delta \ln \mathrm{NO}_{t-1}$	$\Delta \ln \mathrm{NO}_{t-2}$	$\Delta \ln \mathrm{S}_t$	$\Delta \ln \mathrm{S}_{t-1}$	$\Delta \ln \mathrm{S}_{t-2}$	Adjusted R-squared
0.005	0.204	0.112	0.070				0.378
(1.491)	(9.469)	(3.116)	(3.279)				
0.006				0.138	0.137	0.058	0.144
(1.957)				(3.122)	(2.226)	(1.521)	
0.013	0.744	0.508	0.236	-0.783	-0.500	-0.194	0.748
(4.091)	(15.889)	(7.159)	(4.698)	(-10.463)	(-5.144)	(-2.757)	

Table 3: NO/S and the macroeconomy

This table displays regressions in which the dependent variable is $\ln \mathrm{NO/S}_{t+1}$, where NO and S denote new orders and shipments, respectively, of durable goods. Explanatory variables include past growth rates in GDP, consumption (C), fixed investment (I), inventories (N), and unemployment (U), in addition to the term spread, the T-bill rate, the excess stock market return (RMRF), and lagged ln NO/S. All growth rates are computed over four quarters, e.g. $\Delta \ln \mathrm{GDP}_t = \ln \mathrm{GDP}_t - \ln \mathrm{GDP}_{t-4}$. Excess market returns are also computed over four quarters. All quantity data are real and seasonally adjusted, and the sample is from 1958Q2 to 2008Q4. Newey-West t-statistics in parentheses use 6 lags.

#	Intercept	$\Delta \ln \mathrm{GDP}_t$	$\Delta \ln \mathrm{GDP}_{t-4}$	$\Delta \ln \mathrm{C}_t$	$\Delta \ln \mathrm{I}_t$	$\Delta \ln \mathrm{N}_t$	$\Delta \ln \mathrm{U}_t$	Term Spread_t	T-Bill Rate_t	$RMRF_t$	$\ln \mathrm{NO/S}_{t-4}$	Adjusted R-squared
1	0.012	0.614						-8.798	-2.230			0.219
	(1.137)	(4.167)						(-2.716)	(-0.373)			
2	0.002	0.633	0.154					-7.948				0.226
	(0.241)	(4.501)	(1.130)					(-2.471)				
3	0.009	0.592						-9.439		0.027		0.233
	(1.590)	(4.133)						(-3.099)		(1.512)		
4	0.003	0.671						-7.202			0.141	0.235
	(0.424)	(4.351)						(-2.319)			(1.914)	
5	0.020	0.258					-0.065	-8.520				0.244
	(2.661)	(1.252)					(-2.492)	(-2.942)				
6	0.009			0.821	0.087			-9.373				0.224
	(1.273)			(2.921)	(1.346)			(-2.979)				
7	0.016			0.661	-0.041		-7.974	-0.079				0.263
	(2.114)			(2.341)	(-0.666)		(-2.752)	(-3.358)				
8	0.026			0.702	-0.012	-0.341	-0.090	-10.418				0.284
	(3.091)			(2.515)	(-0.197)	(-2.384)	(-3.982)	(-3.370)				
9	0.009			0.729	-0.067	-0.119	-0.100					0.218
	(1.057)			(2.239)	(-0.990)	(-0.769)	(-3.424)					

Table 4: Predictability in GDP growth rates

This table contains the results of restricted versions of the regression

$$\ln \mathrm{GDP}_{t+\tau_2} - \ln \mathrm{GDP}_{t+\tau_1} = \beta_0 + \beta_1 \ln \mathrm{NO/S}_t + \beta_2 \mathrm{TERM}_t + \beta_3 \mathrm{TBILL}_t + \beta_4 \Delta \ln \mathrm{GDP}_t + \beta_5 \Delta \ln \mathrm{NO}_t + \epsilon_t$$

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 2008Q4.

Intercept	ln NO/S	Term Spread	T-Bill Yield	Lag GDP Growth	Lag NO Growth	Adjusted R-Squared
GDP growth from t to $t+1$						
0.008	0.022					0.004
(10.593)	(1.161)					
0.007	0.027	0.875	-0.549	0.227		0.090
(3.534)	(1.390)	(1.349)	(-1.611)	(2.778)		
0.010	-0.007	0.223	-0.482		0.068	0.154
(4.873)	(-0.334)	(0.309)	(-1.450)		(5.162)	
GDP growth from $t+1$ to $t+2$						
0.008	-0.012					-0.003
(11.877)	(-0.693)					
0.007	0.005	1.704	-0.642	0.187		0.112
(3.492)	(0.260)	(2.605)	(-1.912)	(2.174)		
0.009	-0.004	1.494	-0.663		0.028	0.099
(4.550)	(-0.166)	(2.160)	(-1.921)		(1.822)	
GDP growth from $t+2$ to $t+4$						
0.017	-0.082					0.045
(12.454)	(-2.550)					
0.017	-0.051	2.422	-0.987	0.143		0.116
(3.807)	(-1.510)	(1.670)	(-1.317)	(1.187)		
0.019	-0.069	2.065	-0.945		0.037	0.121
(4.386)	(-1.899)	(1.407)	(-1.282)		(1.885)	
GDP growth from $t+4$ to $t+8$						
0.035	-0.193					0.101
(13.283)	(-3.292)					
0.037	-0.142	2.705	-0.791	-0.278		0.117
(4.380)	(-2.530)	(1.158)	(-0.533)	(-1.204)		
0.034	-0.165	2.401	-0.574		0.008	0.106
(3.781)	(-2.328)	(1.053)	(-0.361)		(0.244)	

Table 5: Short-run predictability in industrial production growth rates

This table contains the results of restricted versions of the regression

$$\ln \mathrm{IP}_{t+\tau_2} - \ln \mathrm{IP}_{t+\tau_1} = \beta_0 + \beta_1 \ \ln \mathrm{NO/S}_t + \beta_2 \ \mathrm{TERM}_t + \beta_3 \ \mathrm{TBILL}_t + \beta_4 \Delta \ln \mathrm{IP}_t + \beta_5 \Delta \ln \mathrm{NO}_t + \epsilon_t$$

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 12/2008.

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	0.045					0.031
(4.052)	(3.969)					
0.002	0.037	0.550	-0.348	0.311		0.146
(1.902)	(3.431)	(1.702)	(-2.147)	(5.323)		
0.003	0.046	0.600	-0.450		0.023	0.064
(2.477)	(3.493)	(1.583)	(-2.364)		(1.827)	
			IP growth from $t+1$ to $t+2$			
0.002	0.028					0.011
(4.886)	(2.440)					
0.003	0.032	0.712	-0.508	0.157		0.069
(2.536)	(2.653)	(2.013)	(-2.640)	(2.861)		
0.004	0.031	0.674	-0.550		0.021	0.053
(3.059)	(2.421)	(1.812)	(-2.827)		(1.558)	
			IP growth from $t+2$ to $t+3$			
0.002	0.016					0.002
(5.697)	(1.256)					
0.003	0.022	0.916	-0.574	0.161		0.075
(2.794)	(1.555)	(2.688)	(-2.970)	(2.332)		
0.004	0.019	0.838	-0.607		0.026	0.061
(3.335)	(1.264)	(2.385)	(-3.134)		(2.167)	

Table 6: Correlation matrix of predictive variables

This table contains the correlation matrix of the eight variables used in our predictive return regressions. In addition to the predictors described in Tables 1 and 4, these include the output gap measured using the approach of Cooper and Priestley (2008); the earnings yield, or the most recent 4 quarters of earnings divided by the current level of the S&P Composite; the *cay* variable from Lettau and Ludvigson (2001); and the default spread, measuring the difference between BAA and Treasury yields. In order to account for reporting delays, the macro-based variables (ln NO/S, the output gap, and *cay*) are lagged one month relative to the other predictors. All data are monthly from 2/1958 to 12/2008.

	ln NO/S	Output Gap	Earnings Yield	*cay*	Term Spread	Default Spread	T-Bill Yield
ln NO/S	1.000	0.371	0.125	-0.236	-0.369	-0.355	0.191
Output Gap	0.371	1.000	-0.007	-0.596	-0.541	-0.164	0.116
Earnings Yield	0.125	-0.007	1.000	-0.057	-0.133	0.023	0.752
cay	-0.236	-0.596	-0.057	1.000	0.318	-0.069	-0.046
Term Spread	-0.369	-0.541	-0.133	0.318	1.000	0.448	-0.345
Default Spread	-0.355	-0.164	0.023	-0.069	0.448	1.000	-0.008
T-Bill Yield	0.191	0.116	0.752	-0.046	-0.345	-0.008	1.000

Table 7-A: Predictability in excess stock market returns

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 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, 4, and 6. Values in parentheses are t-statistics computed from Newey-West standard errors. The number of lags used in the four panels of the table are 1, 5, 18, and 18, respectively. Data are from 2/1958 to 12/2008.

Intercept	ln NO/S	Output Gap	Earnings Yield	*cay*	Term Spread	Default Spread	T-Bill Yield	Adjusted R-Squared
				Return during first month				
0.005	-0.096							0.004
(2.300)	(-1.678)							
-0.002		-0.044	0.403	0.277	-2.241	1.966	-4.655	0.034
(-0.346)		(-1.257)	(3.072)	(1.949)	(-0.802)	(0.411)	(-2.812)	
-0.001	-0.036	-0.040	0.404	0.269	-2.267	1.311	-4.584	0.033
(-0.149)	(-0.527)	(-1.129)	(3.101)	(1.877)	(-0.815)	(0.254)	(-2.737)	
				Return during first quarter				
0.017	-0.435							0.033
(2.953)	(-3.121)							
-0.009		-0.116	1.096	0.939	-6.297	6.742	-12.124	0.092
(-0.522)		(-1.251)	(3.512)	(2.625)	(-0.969)	(0.541)	(-3.011)	
0.001	-0.321	-0.078	1.102	0.852	-6.389	0.453	-11.386	0.105
(0.074)	(-1.897)	(-0.814)	(3.704)	(2.355)	(-1.005)	(0.034)	(-2.844)	
				Return during first year				
0.062	-1.257							0.073
(3.551)	(-3.114)							
-0.045		-0.138	3.307	3.418	2.728	15.108	-33.603	0.263
(-0.878)		(-0.431)	(3.876)	(2.756)	(0.158)	(0.486)	(-3.701)	
-0.017	-0.798	-0.048	3.277	3.195	3.309	-3.488	-30.839	0.283
(-0.339)	(-2.790)	(-0.146)	(4.025)	(2.624)	(0.194)	(-0.113)	(-3.270)	

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

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 Lehman (Ibbotson before 2/1973) long-term Treasury index and the contemporaneous return on a 1-month Treasury bill. Returns during 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, 4, and 6. Values in parentheses are t-statistics computed from Newey-West standard errors. The number of lags used in the four panels of the table are 1, 5, 18, and 18, respectively. Data are from 2/1958 to 12/2008.

Intercept	ln NO/S	Output Gap	Earnings Yield	*cay*	Term Spread	Default Spread	T-Bill Yield	Adjusted R-Squared
				Return during first month				
-0.002	-0.070							0.006
(-1.652)	(-2.275)							
-0.007		0.016	0.022	0.007	4.055	-0.996	-0.306	0.007
(-1.304)		(0.779)	(0.272)	(0.063)	(1.941)	(-0.284)	(-0.269)	
-0.005	-0.057	0.023	0.025	-0.007	4.014	-2.017	-0.196	0.010
(-0.901)	(-1.405)	(1.078)	(0.296)	(-0.070)	(1.937)	(-0.530)	(-0.170)	
				Return during first quarter				
-0.007	-0.179							0.015
(-2.255)	(-2.343)							
-0.007		0.027	-0.199	-0.195	15.486	-13.178	2.627	0.047
(-0.665)		(0.485)	(-0.953)	(-0.802)	(3.527)	(-2.527)	(1.064)	
-0.001	-0.197	0.050	-0.195	-0.248	15.429	-17.041	3.080	0.060
(-0.077)	(-2.265)	(0.912)	(-0.934)	(-1.024)	(3.626)	(-3.047)	(1.269)	
				Return during first year				
-0.032	-0.575							0.046
(-2.954)	(-2.564)							
-0.009		-0.037	-1.110	-0.708	45.979	-46.716	12.410	0.160
(-0.231)		(-0.174)	(-1.529)	(-1.030)	(3.555)	(-2.496)	(1.580)	
0.015	-0.662	0.038	-1.135	-0.893	46.460	-62.153	14.705	0.204
(0.388)	(-2.600)	(0.187)	(-1.651)	(-1.327)	(3.681)	(-3.151)	(2.021)	

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

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 Lehman (Ibbotson before 2/1973) intermediate-term Treasury index and the contemporaneous return on a 1-month Treasury bill. Returns during 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, 4, and 6. Values in parentheses are t-statistics computed from Newey-West standard errors. The number of lags used in the four panels of the table are 1, 5, 18, and 18, respectively. Data are from 2/1958 to 12/2008.

Intercept	ln NO/S	Output Gap	Earnings Yield	*cay*	Term Spread	Default Spread	T-Bill Yield	Adjusted R-Squared
				Return during first month				
-0.003	-0.046							0.015
(-4.356)	(-3.154)							
0.001		0.003	0.000	-0.020	0.397	-1.137	-0.596	0.008
(0.332)		(0.283)	(-0.010)	(-0.470)	(0.448)	(-0.942)	(-1.294)	
0.003	-0.060	0.010	0.002	-0.035	0.353	-2.226	-0.478	0.029
(1.175)	(-3.280)	(1.047)	(0.053)	(-0.817)	(0.409)	(-1.635)	(-1.031)	
				Return during first quarter				
-0.008	-0.102							0.023
(-4.890)	(-2.376)							
0.007		0.000	-0.112	-0.130	2.268	-6.897	-0.370	0.047
(1.215)		(-0.002)	(-1.121)	(-1.121)	(1.109)	(-2.676)	(-0.298)	
0.012	-0.158	0.019	-0.109	-0.172	2.222	-9.999	-0.006	0.089
(2.245)	(-3.354)	(0.653)	(-1.089)	(-1.537)	(1.149)	(-3.634)	(-0.005)	
				Return during first year				
-0.035	-0.278							0.036
(-4.765)	(-1.827)							
0.039		-0.034	-0.576	-0.427	4.810	-28.421	-0.839	0.198
(1.846)		(-0.294)	(-1.512)	(-1.127)	(0.816)	(-2.783)	(-0.210)	
0.056	-0.503	0.023	-0.595	-0.568	5.175	-40.140	0.903	0.283
(2.826)	(-3.147)	(0.216)	(-1.685)	(-1.561)	(0.914)	(-3.913)	(0.254)	

Table 7-D: Predictability in excess corporate bond returns

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 Lehman (Ibbotson before 2/1973) investment-grade corporate bond index and the contemporaneous return on a 1-month Treasury bill. Returns during 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, 4, and 6. Values in parentheses are t-statistics computed from Newey-West standard errors. The number of lags used in the four panels of the table are 1, 5, 18, and 18, respectively. Data are from 2/1958 to 12/2008.

Intercept	ln NO/S	Output Gap	Earnings Yield	*cay*	Term Spread	Default Spread	T-Bill Yield	Adjusted R-Squared
				Return during first month				
-0.002	-0.108							0.020
(-1.552)	(-3.437)							
-0.007		0.007	0.075	0.094	2.773	1.075	-1.360	0.022
(-1.414)		(0.410)	(0.868)	(0.942)	(1.363)	(0.292)	(-1.184)	
-0.005	-0.077	0.017	0.078	0.075	2.717	-0.319	-1.209	0.029
(-0.904)	(-2.035)	(0.907)	(0.893)	(0.743)	(1.347)	(-0.081)	(-1.038)	
				Return during first quarter				
-0.007	-0.287							0.045
(-2.279)	(-3.840)							
-0.008		-0.001	-0.080	0.022	12.674	-8.913	0.160	0.057
(-0.725)		(-0.014)	(-0.379)	(0.094)	(2.858)	(-1.461)	(0.065)	
0.001	-0.267	0.031	-0.075	-0.050	12.597	-14.147	0.774	0.085
(0.053)	(-3.216)	(0.597)	(-0.357)	(-0.216)	(2.963)	(-2.344)	(0.325)	
				Return during first year				
-0.029	-0.940							0.112
(-2.616)	(-3.771)							
-0.025		-0.070	-0.729	-0.115	43.442	-25.375	3.655	0.192
(-0.561)		(-0.350)	(-0.864)	(-0.170)	(3.886)	(-1.291)	(0.460)	
0.003	-0.798	0.021	-0.759	-0.338	44.023	-43.986	6.422	0.250
(0.075)	(-3.084)	(0.113)	(-0.944)	(-0.519)	(4.096)	(-2.227)	(0.874)	

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

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 Lehman (Ibbotson before 5/1990) high yield bond index and the contemporaneous return on a 1-month Treasury bill. Returns during 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, 4, and 6. Values in parentheses are t-statistics computed from Newey-West standard errors. The number of lags used in the four panels of the table are 1, 5, 18, and 18, respectively. Data are from 2/1958 to 12/2008.

Intercept	ln NO/S	Output Gap	Earnings Yield	*cay*	Term Spread	Default Spread	T-Bill Yield	Adjusted R-Squared
				Return during first month				
0.000	-0.097							0.017
(0.335)	(-3.098)							
-0.012		-0.031	0.171	0.065	1.449	1.940	-1.155	0.036
(-2.848)		(-1.920)	(2.335)	(0.721)	(0.909)	(0.535)	(-1.121)	
-0.010	-0.058	-0.024	0.173	0.051	1.407	0.902	-1.043	0.039
(-2.130)	(-1.390)	(-1.408)	(2.388)	(0.561)	(0.895)	(0.227)	(-0.993)	
				Return during first quarter				
0.001	-0.295							0.039
(0.305)	(-3.304)							
-0.035		-0.081	0.380	0.191	6.954	3.205	-1.336	0.083
(-3.205)		(-1.776)	(2.001)	(0.737)	(1.672)	(0.318)	(-0.465)	
-0.028	-0.195	-0.058	0.383	0.138	6.898	-0.618	-0.887	0.094
(-2.375)	(-1.740)	(-1.212)	(2.048)	(0.533)	(1.702)	(-0.056)	(-0.304)	
				Return during first year				
0.005	-0.966							0.103
(0.396)	(-4.161)							
-0.142		-0.242	1.010	0.006	38.565	14.483	0.480	0.302
(-3.449)		(-1.356)	(1.753)	(0.007)	(3.619)	(0.670)	(0.070)	
-0.123	-0.542	-0.181	0.990	-0.146	38.959	1.839	2.360	0.325
(-3.061)	(-2.398)	(-1.049)	(1.778)	(-0.178)	(3.764)	(0.081)	(0.352)	

Table 8: Out-of-sample return predictability R-squares

This table contains results from regressing nonoverlapping quarterly excess returns on lagged values of ln NO/S. Following an initialization period of 5, 10, or 20 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 (2005), 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. Data are from 1958Q2 to 2008Q4.

	Without positivity restriction			With positivity restriction		
Initialization period	5 years	10 years	20 years	5 years	10 years	20 years
Excess stock market return	0.0222	0.0225	-0.0083	0.0306	0.0319	0.0186
Excess long-term Treasury bond return	0.0159	0.0168	0.0137	0.0008	0.0008	-0.0003
Excess intermediate-term Treasury bond return	0.0091	0.0151	-0.0082	0.0105	0.0144	-0.0098
Excess corporate bond return	0.0533	0.0553	0.0308	0.0104	0.0123	0.0029
Excess high yield bond return	0.0467	0.0475	0.0299	0.0401	0.0413	0.0356

Table 9: Does NO or S drive predictability in excess returns?

This table contains results from regressing future excess returns on ln NO/S, ln NO*, and/or ln S*, where the latter two series are detrended versions of ln NO and ln S. The trend, which is assumed to be the same for both series, is estimated by applying a one-sided Hodrick-Prescott filter to the average of ln NO and ln S. The excess return is defined as the difference between the continuously compounded return on the asset class listed and the contemporaneous return on a 1-month Treasury bill. Dependent variables are overlapping quarterly returns, computed by summing the first 3 monthly returns following the forecast date. Values in parentheses are t-statistics computed from Newey-West standard errors using 5 lags. P-values from a test of the equality of the coefficients on ln NO* and ln S* are included in the last column. Data are from 2/1958 to 12/2008, but the first two years of data are only used to initialize the filter and are not included in the regressions.

Intercept	ln NO/S	ln NO*	ln S*	Adjusted R-Squared	P-Val. of Eq. Restriction
			Stocks		
0.015	-0.429			0.031	
(2.629)	(-2.939)				
0.010		-0.217		0.017	
(1.813)		(-2.388)			
0.009			-0.044	-0.001	
(1.680)			(-0.297)		
0.015		-0.434	0.368	0.030	0.625
(2.651)		(-2.964)	(1.776)		
			Long-term Treasury bonds		
-0.007	-0.196			0.018	
(-2.164)	(-2.452)				
-0.010		-0.040		0.000	
(-3.130)		(-0.674)			
-0.009			0.075	0.002	
(-3.010)			(0.929)		
-0.007		-0.191	0.257	0.019	0.405
(-2.011)		(-2.387)	(2.251)		
			Corporate bonds		
-0.007	-0.293			0.045	
(-2.326)	(-3.707)				
-0.011		-0.044		0.001	
(-3.491)		(-0.740)			
-0.010			0.137	0.013	
(-3.321)			(1.548)		
-0.006		-0.285	0.409	0.054	0.133
(-2.040)		(-3.635)	(3.405)		

Table 10: Stock return predictability by sector

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. Non-manufacturing consists of SIC codes between 01 and 17 and between 40 and 89. "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. Newey-West t-statistics, displayed in parentheses, are computed using 1, 5, and 18 lags for monthly, quarterly, and annual regressions. Data are from 2/1958 to 12/2008.

	Without controls				With controls		
	ln NO/S				ln NO/S		
	Coef	T-Stat	R^2		Coef	T-Stat	R^2
			Non-durable manufacturing				
M	-0.076	-1.446	0.003	M	-0.012	-0.201	0.027
Q	-0.310	-2.485	0.022	Q	-0.176	-1.262	0.088
A	-0.865	-2.262	0.043	A	-0.442	-1.720	0.216
			Durable manufacturing				
M	-0.097	-1.385	0.002	M	-0.021	-0.243	0.024
Q	-0.539	-3.183	0.029	Q	-0.404	-1.903	0.086
A	-1.644	-3.429	0.070	A	-1.054	-2.597	0.238
			Non-manufacturing				
M	-0.126	-2.200	0.008	M	-0.077	-1.114	0.035
Q	-0.467	-3.345	0.038	Q	-0.367	-2.247	0.108
A	-1.338	-3.297	0.083	A	-0.934	-3.171	0.300
			Durable manufacturing minus non-durable manufacturing				
M	-0.021	-0.502	-0.001	M	-0.008	-0.161	-0.002
Q	-0.229	-2.641	0.012	Q	-0.228	-1.971	0.026
A	-0.779	-2.489	0.032	A	-0.612	-1.774	0.092
			Durable manufacturing minus non-manufacturing				
M	0.028	0.826	-0.001	M	0.056	1.449	0.001
Q	-0.073	-0.909	0.001	Q	-0.037	-0.408	0.015
A	-0.307	-1.141	0.007	A	-0.121	-0.418	0.070

Table 11: Aggregate vs. industry NO/S

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 2008Q4.

——— 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
-0.560		0.024	-0.399		0.079
(-2.324)			(-1.433)		
	-0.125	0.004		-0.028	0.071
	(-1.378)			(-0.372)	
-0.602	0.046	0.025	-0.452	0.065	0.080
(-2.507)	(0.739)		(-1.619)	(1.196)	

Table 12: Key return and macro moments

This table reports the aggregate return and macro moments used to calibrate the model. The Sharpe ratio, risk free rate, and average excess stock returns are from Storesletten, Telmer, and Yaron (2007). The volatility of output growth and NO/S are from our calculations over the post-war and post-1958 samples, respectively. All values are annualized.

Moment	Value
Average excess stock returns	6.8%
Unconditional Sharpe ratio	0.41
Average risk free rate	1.3%
Volatility of output growth	1.0%
Volatility of ln NO/S	3.5%

Table 13: Model parameter values and predictive regressions

Panel A of this table reports parameter values that are fixed across all three calibrations of our model to the moments in Table 12. In Panel B we report the other three parameters, which differ across calibrations, as well as the model-implied slope coefficients and R-squares from the regression

$$r^e_{t+1} = \alpha_0 + \alpha_1 \ln \mathrm{NO/S}_t + \epsilon_{t+1}$$

where r^e_{t+1} denotes the excess return of the firm.

Panel A: Fixed parameter values

θ	δ	σ_a	β	γ_0
0.36	0.025	0.015	0.997	2.6

Panel B: Model-implied risk premia and predictive regressions

γ_1	ρ_x	ξ	α_1	R^2
-25.0	0.7	58	-0.31	3.3%
-19.0	0.8	67	-0.24	1.7%
-13.0	0.9	75	-0.16	0.6%

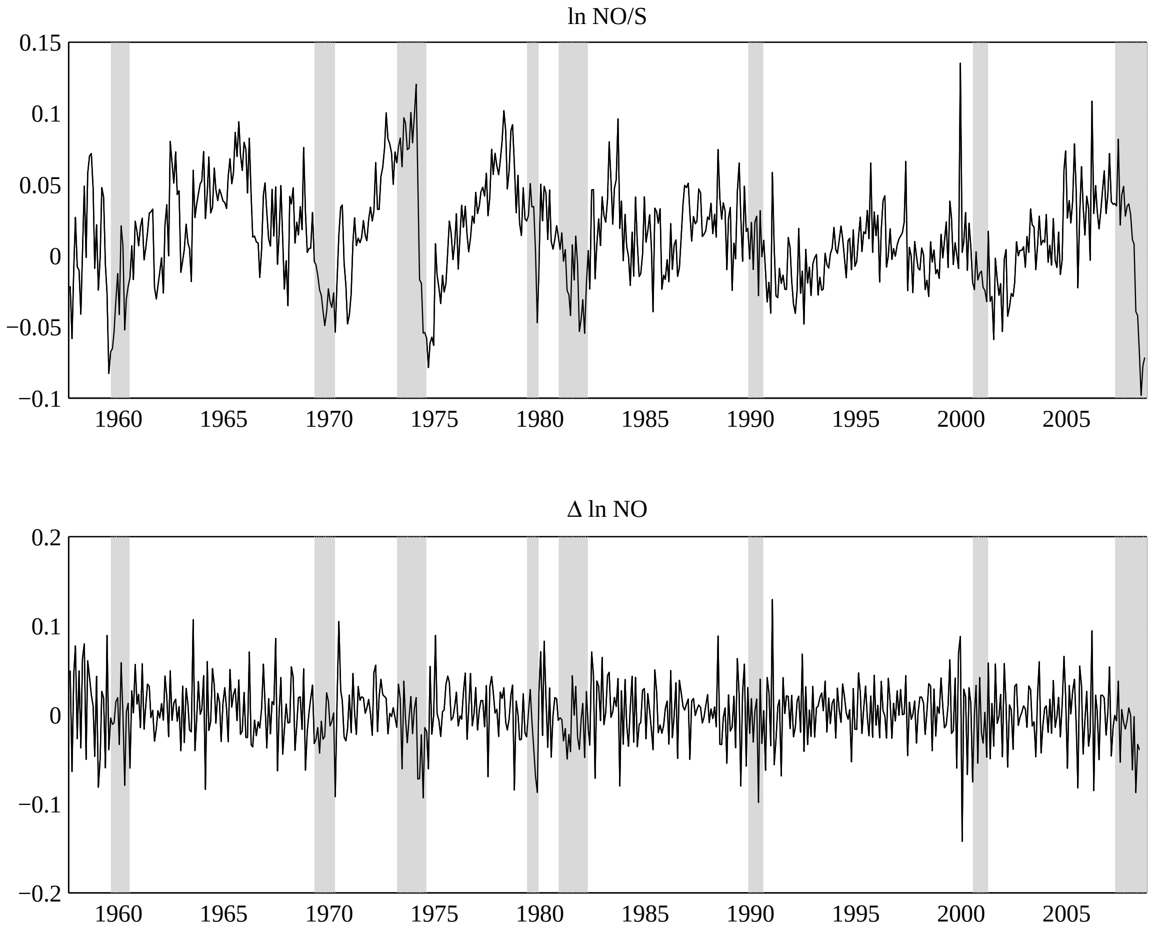

Figure 1. The top panel of this figure plots the logarithm of the ratio of new orders of durable goods to shipments of durable goods. The bottom panel plots growth rates of the new orders series. Shaded areas denote NBER recessions. Data are monthly from 2/1958 to 12/2008.

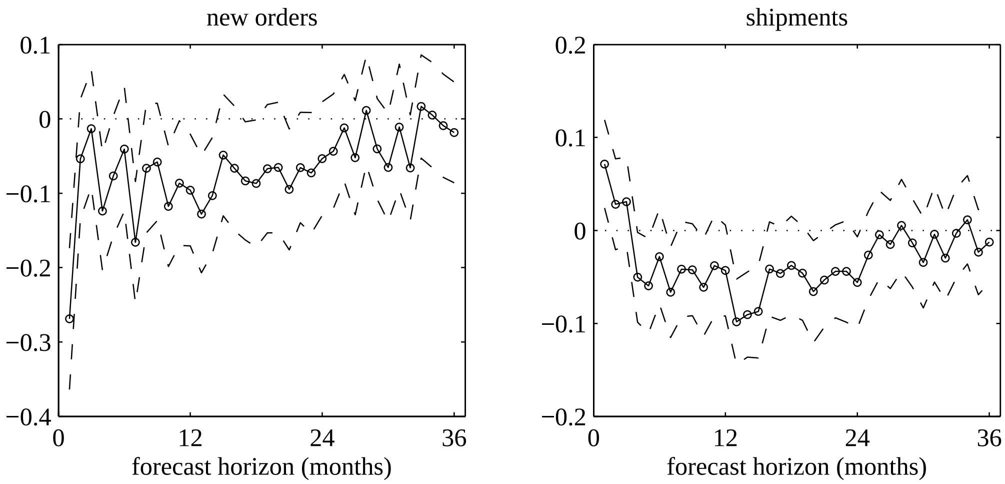

Figure 2. Each panel of this figure plots the slope coefficients and 95% confidence intervals from the regression of some output growth measure on lagged ln NO/S, i.e.

$$\ln \mathrm{Y}_{t+\tau} - \ln \mathrm{Y}_{t+\tau-1} = \alpha + \beta \, \ln \mathrm{NO/S}_t + \epsilon_t$$

where Y either denotes new orders or shipments of durable goods. Values of τ are given on the horizontal axis, denoting the forecast horizon. Newey-West standard errors are computed using one lag. Data are monthly from 2/1958 to 12/2008.

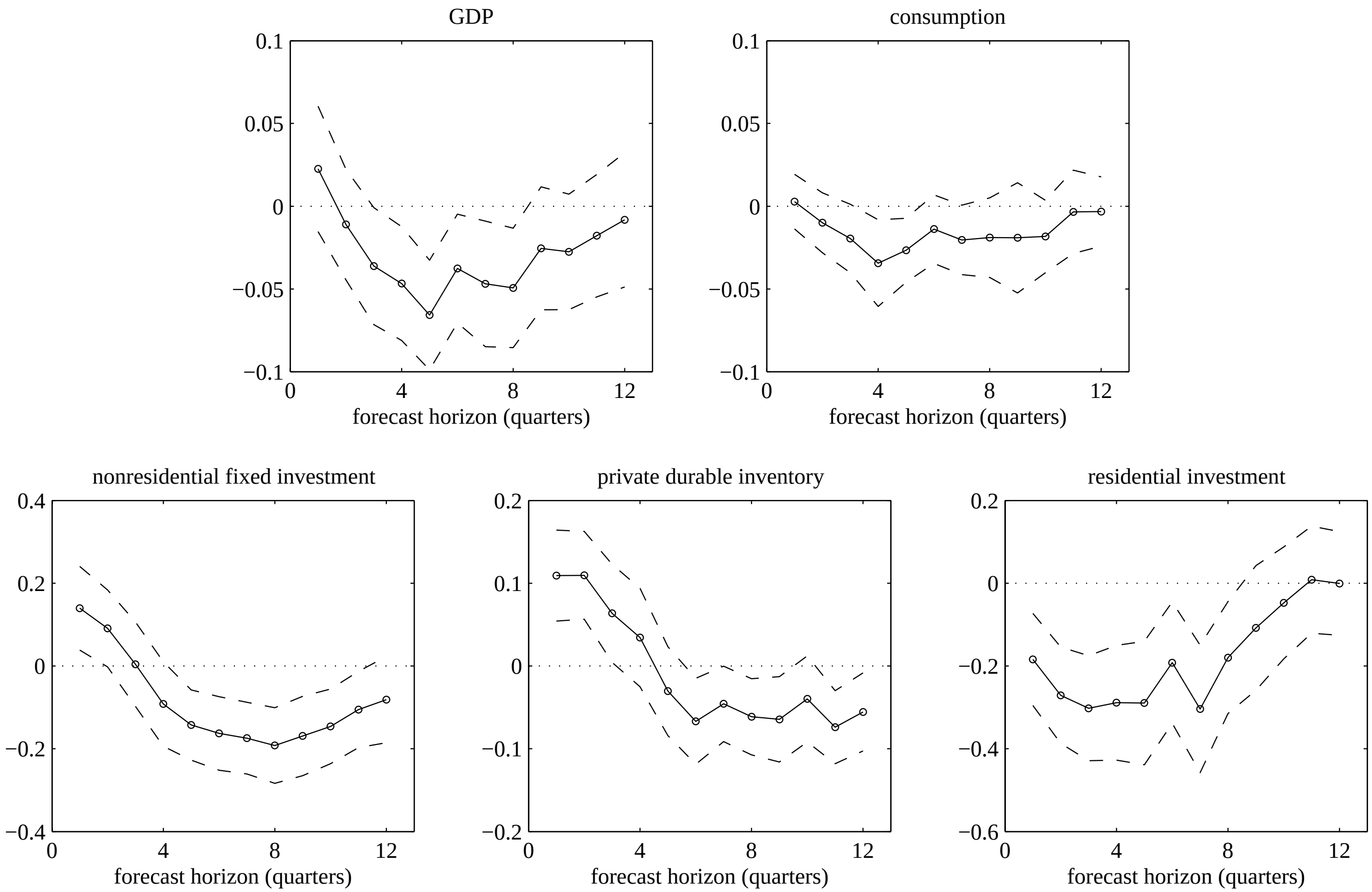

Figure 3. Each panel of this figure plots the slope coefficients and 95% confidence intervals from the regression of some output growth measure on lagged ln NO/S, i.e.

$$\ln \mathrm{Y}_{t+\tau} - \ln \mathrm{Y}_{t+\tau-1} = \alpha + \beta \ \ln \mathrm{NO/S}_t + \epsilon_t$$

where Y denotes GDP, per capita consumption, nonresidential fixed investment, private durable inventories, or residential investment (defined as residential structures investment plus durable consumption expenditures). Values of τ are given on the horizontal axis, denoting the forecast horizon. Newey-West standard errors are computed using one lag. Data are quarterly from 1958Q2 to 2008Q4.

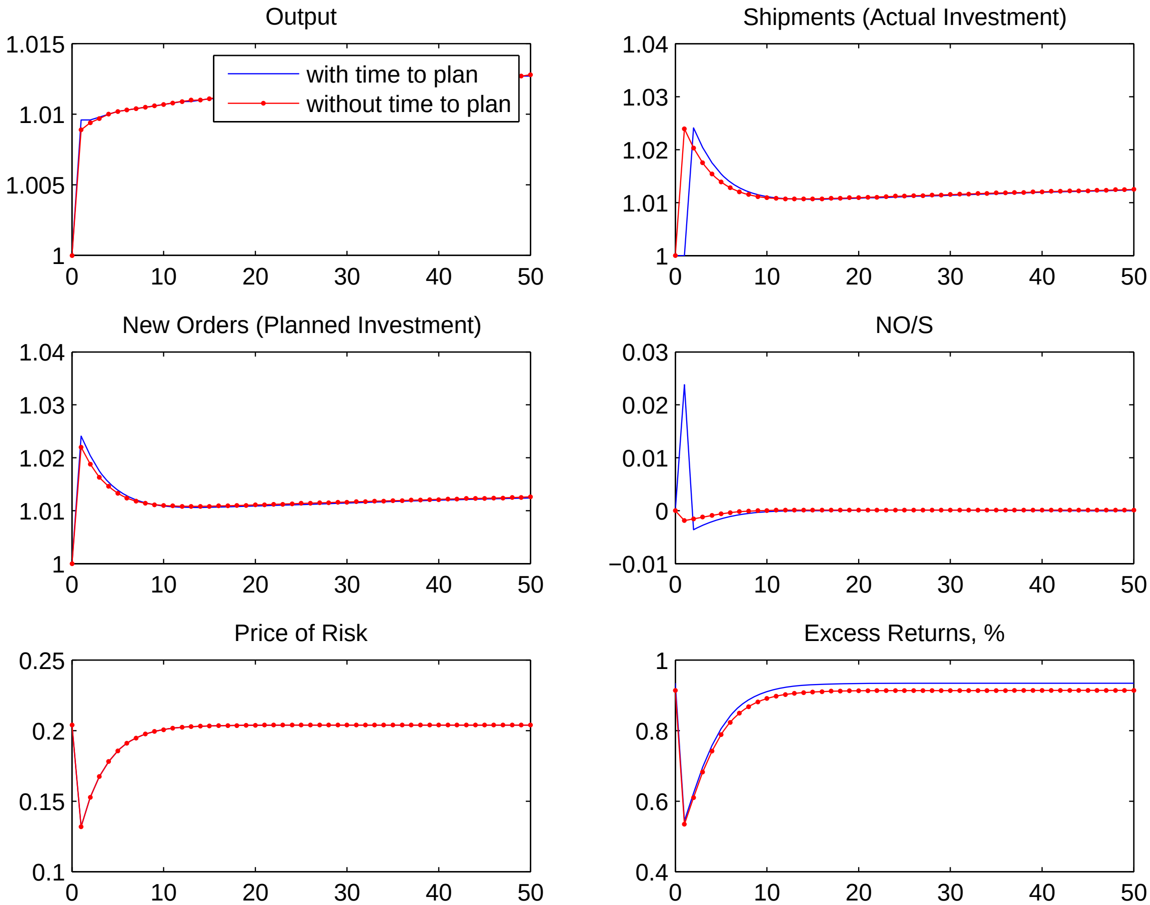

Figure 4. Impulse response functions for models with and without time to plan. This figure displays the responses to a one standard deviation shock to aggregate productivity at horizons from 1-50 quarters. Real variables (output, shipments, and new orders) are normalized to have a unit quantity at time zero, and the shock occurs at time one. Time zero values of NO/S, the price of risk, and the risk premium are steady state values.

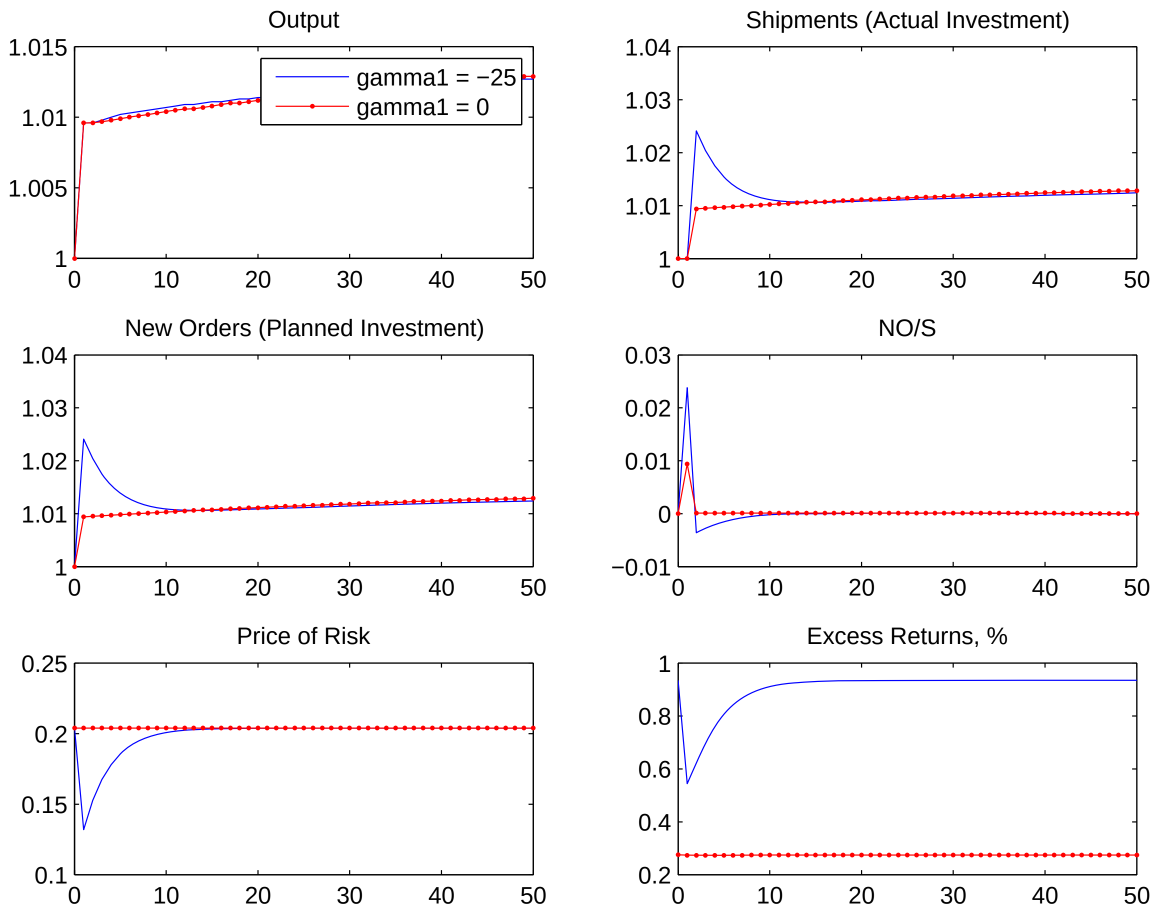

Figure 5. Impulse response functions for models with and without time-varying risk premia. This figure displays the responses to a one standard deviation shock to aggregate productivity at horizons from 1-50 quarters, both for the benchmark model with time-varying risk premia ($\gamma_1 = -25$) and an alternative model in which the price of risk is constant ($\gamma_1 = 0$). Real variables (output, shipments, and new orders) are normalized to have a unit quantity at time zero, and the shock occurs at time one. Time zero values of NO/S, the price of risk, and the risk premium are steady state values.