Predictability of Stock Market Excess Returns With Household's Obligation Ratio

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In this study, I test the predictability of stock market excess returns with households' obligations ratio. Using U.S stock market data, I show that household's debt service ratio can predict stock market returns at short horizon and over business cycle frequencies. I show that between 1980 and 2016, mean deviations from debt service ratio is a better forecaster of future returns both in-sample and out-of-sample than dividend-price ratio, dividend yield, earnings-price ratio, investment-capital ratio, and several other popular forecasting variables. The results remain significant using quarterly data and annual data.

Keywords: asset pricing, excess returns predictability, household financial obligations ratio

INTRODUCTION

Household's obligation ratio is defined as total debt payments, housing payments and auto lease payments divided by total disposable income. It is a macroeconomic counter-cyclical variable that helps explaining the equity risk premium observed in U.S data (Jahangiry, 2020). Jahangiry shows that households' financial obligations impact the equity risk premium via two channels, the preference channel, and the borrowing constraint channel. In his set up, individuals' preferences are defined over consumption relative to financial obligations. The framework is analogous to habit formation models where the utility function depends on consumption relative to some habit level (Abel (1990), Constantinides (1990) and Campbell and Cochrane (1999)). On the other hand, in an infinite horizon aggregate household economy, financial obligation ratio represents the borrowing constraint since the agents' borrowing capability is limited by their financial obligation ratio in the model.

The mechanism behind why financial obligation ratio help explaining the equity risk premium is straight forward. In bad times when consumption is low, mostly because of lower income and more borrowing incentives, the financial obligation ratio is high. This dynamic borrowing constraints become binding in states of the economy when the agents really need to smooth their consumption. This is the borrowing constraint channel. From the other hand, there is the preference channel. As consumption rises in good times, households slowly take on more debt. In bad times consumption falls and households will delever slowly. Thus, debt moves slowly, following consumption. (This is much like slow-moving habit). Now suppose an agent has taken on a specific level of debt which he must repay. In recessions, as income declines towards this specific level of debt, to make sure that he can repay the debt, the investor will become more risk averse and take on less risk. This decreases the demand for risky assets and increases the demand for precautionary savings in recessions. During booms however, consumption gets further away from the slow-moving financial obligations and hence the investor will become less risk averse and take on more risk.

Thus, lower ratio of consumption relative to financial obligation in recessions and higher ratio in good times will directly impact the marginal utility and make the pricing kernel more volatile. These two separate channels are the key ingredients of Jahangiry's model in explaining the equity risk premium. It has also been documented that the risk associated with aggregate households' financial obligations is an economy-wide risk and significant for explaining the variations in cross-section of stock returns (Jahangiry, 2019). Conditioning down on financial obligation ratio, the financial obligation capital asset pricing model (FCAPM) proposed by Jahangiry, survives a wide range of classical econometric and diagnostic tests on explaining the variations in average returns across 25 portfolios formed based on size and book to market ratio.

The consistent pricing of financial obligation risk with a negative risk premium suggests that financial obligation ratio acts as a state variable rather than being just another statistical factor. The cross-sectional intuition is as follows. In bad times, financial obligation ratio is high and marginal utility of consumption is also high. Portfolios which pay off in these times are more valuable assets to the investors. The increase in hedging demands for these portfolios raise the prices and hence imply a lower expected return. The negative financial obligation risk premium will deliver this lower expected return for the asset that its payoff is positively correlated with financial obligation ratio.

In this study, I investigate the predictability of stock market excess returns with household's obligation ratios, namely debt service ratio and financial obligations ratio. For the last two decades there have been so many efforts to identify and establish the existence of time variation in expected asset returns; it is now widely accepted that excess returns are predictable by variables such as dividend–price ratios, earnings–price ratios, dividend–yield ratios, investment-capital ratio, and other financial indicators.

However, these financial variables have been successful at predicting long horizon returns, but less successful at predicting returns at shorter horizons. Dividend–price ratios, earnings–price ratios and all other predictive variables are **financial** variables. We are also interested in linkage between **macroeconomic** variables and financial markets mostly because expected returns appear to vary with business cycles so the stock market returns should be forecastable by business cycle variables at cyclical frequencies. One macroeconomic business cycle variable which is successful at predicting returns at shorter horizon is consumption-wealth ratio (aka cay) proposed by Lettau and Ludvigson 2001. Lettau and Ludvigson study the role of fluctuations in the aggregate consumption wealth ratio for predicting stock returns. Using U.S. quarterly stock market data, they find that these fluctuations in the consumption–wealth ratio are strong predictors of both real stock returns and excess returns over a Treasury bill rate. However, the statistical significance and predictability power of consumption-wealth ratio is hump shaped and peaks around one year. Indeed, the predictability power shrinks over long horizon. In this study I show that mean-deviations from household's obligation ratio is yet another macroeconomic business cycle variable that its predictability power is significant at short horizons and remains more significant over longer horizons than does consumption-wealth ratio.

But why should mean deviations from household's obligation ratio have any predictive power? The economic intuition is laid out as follows. In early stages of recessions, when returns are expected to be lower in the near future, households will allow (must admit!) that their obligation ratios go above its long run average. This is true because households' obligations behave like slow-moving habit (with no-default assumption of course!); in good times households pile up more obligations which they must commit to in bad times as well. This, along with negative income shocks in recessions will eventually leave households with higher obligation ratios. The opposite is the case for good times. During booms, households receive positive income shocks, this will allow them to experience lower obligations ratios. Note that households' obligations may increase during booms, but higher income shocks will offset these effects and the overall obligation ratio will be lower. Hence, lower expected future returns are followed by higher obligation ratios and vice versa. This suggests that deviations of obligation ratio from its mean should be negatively correlated to future returns which is consistent with what I find in this paper.

The rest of the paper is as follows. In the next section, I will discuss what is the household's obligation ratio and why it matters. In the data section, I present the data and summary statistics. Then I move on to test the predictability of stock returns with mean deviations from household's obligation ratio. The following sections document findings on long-horizon forecasts and on out-of-sample tests. Finally, last section concludes.

HOUSEHOLDS' OBLIGATION RATIO

Household's obligation ratio is defined as household's total obligations divided by total disposable income. In its most comprehensive definition, household's obligations are all **financial** obligations including **debt service payments** and **consumer debt payments**. In this paper, I will use obligation ratio interchangeably both for Financial Obligation Ratio (*FOR*) and Debt Service Ratio (*DSR*) as the correlation between the two is very high and they both capture the same idea.

What Is Financial Obligation Ratio and Why Does It Matter?

Households' Financial obligations ratio is defined as the households' total financial obligations divided by their total disposable income. Financial obligation ratio consists of two parts:

1. **Total debt service ratio**, which is equal to total debt payments divided by total disposable income. Debt payments include all the mortgage debt payments and consumer debt payments including auto loans, student loans, consumer credit cards etc.
2. **Total financial commitment ratio**, which is equal to total financial commitments divided by total disposable income. Financial commitments include all the rent payments, lease payments, insurance, and property tax payments of the homeowners.

Financial obligations affect individuals' consumption behavior. There is a huge documentation in economic psychology literature studying the psychological impacts of being in debt. Indeed, financial obligations are associated with high levels of anxiety and stress (Brown, Taylor, and Price (2005), Richardson, Elliott, and Roberts (2013)). More importantly This impact is independent of the poverty with which it is often associated (Jenkins, Bhugra, Bebbington, and Farrell (2008), Meltzer, Bebbington, Brugha, and Dennis (2011)). Financial obligations also impact households' budget constraints. If these obligations are high relative to income, and it is not possible to roll over the debt, then borrowers must cut back on expenditure to avoid default. There is evidence that high financial obligations reduce expenditure at the micro level. In fact, the negative effect of a high debt service burden on consumption of households has been shown by Olney (1999), Johnson and Li (2010), Dynan (2012) and Juseliuse and Drehmann (2015). Further the household's financial obligation position is important in determining whether the household is constrained from optimal consumption smoothing. The fact that a household may have been able to borrow in the past does not imply that it can borrow as much in the future. Hence, financial obligation ratio can be used as a direct indicator of borrowing constraints. Below, I review some important properties of the household's obligations ratio.

Properties of Household's Obligation Ratio

Since 1980 onward, Federal Reserve Board has reported the financial obligation ratio for U.S households. As we can observe in FIGURE 1, households' financial obligation ratio as a percentage of disposable personal income is a time varying macroeconomic variable with the average of 16.48% which tends to move counter-cyclically over the business cycles. As the economy stays in good times, consumers keep spending more and hence increasing their financial obligation, now when the economy is hit by a negative income shock (recession) this is the time that financial obligations are already large, and people cannot smooth their consumption exactly when they need to do so. Hence what we observe in the data is that financial obligation ratio is high almost in the early stage of every recession because households are carrying many obligations from previous good old days and then the ratio decreases as the economy recovers. FIGURE 1 shows that almost after every recession, the financial obligation ratio pulls back to lower levels which is true because of both households' higher incomes and de-levering during booms. Also, when household obligations ratios are high and unemployment is rising, lenders may respond to the expected increase in defaults by limiting the availability of credit and this leads to lower aggregate payments and finally lower financial obligation ratio. Thus, financial obligation ratio has a counter-cyclical property.

Shaded areas in FIGURE 1 indicate US recessions. Other important properties of financial obligation ratio which make it a variable of interest are as follows:

- All the components of the financial obligation ratio are **observable** so when working with data, there is no need to come up with questionable proxies.
- Financial obligation ratio is **directly** related to the interest rate. By construction, the higher the interest rate, the higher the payments and the higher the financial obligations. This explicit dependence on the interest rate establishes a direct link between obligation ratios and predictability of stock market returns. Juselius and Drehmann (2015) argue that "the average lending rate reflects not only current interest rate conditions, but also past money market rates, past inflation and interest rate expectations as well as past risk and term premia. This implies that the lending rate, and hence the debt service ratio, is chiefly influenced by current and past monetary policy decisions".

FIGURE 1
FINANCIAL OBLIGATIONS RATIO AS A PERCENT OF DISPOSABLE INCOME

- Financial obligation ratio captures the obligations burden on households more accurately than the established leverage ratio, the debt-to-GDP ratio. More specifically financial obligation ratio accounts for changes in *interest rates* and *maturities* that affect households' repayment capacity.
- Drehmann and Juselius (2012) found that the debt service ratio (which is the main part of financial obligation ratio) produces a very reliable early warning signal ahead of systemic banking crises. In the context of asset pricing this is important because we are looking for a conditioning down variable which is correlated with business cycles specially with "bad times".
- Financial obligation ratio can be used as a direct indicator of borrowing constraints. Johnson and Li (2010) tested the proposition that a higher debt service ratio increases the likelihood of credit denial. So, household's obligation ratio is a critical input for lending institutions to provide agents with more leverage.

The linkage between financial obligations ratio as a business cycle macroeconomic variable and predictability of stock market returns is the central question of interest in this paper. Given the properties for financial obligation ratio and the fact that expected returns vary with business cycles, we are going to explore if the deviations from the obligation ratios have any predictability power at cyclical frequencies. Next section provides the summary statistics for these deviation and other variables.

DATA AND SUMMARY STATISTICS

In this paper, one key advantage with respect to the data is that all the variables are directly observable and there is no need to work with any questionable proxies. The data include stock market returns and dividends per share from the Standard & Poor's Composite Index. We also consider returns on the value weighted CRSP Index as it provides a better and broader proxy for total asset wealth than does the *S&P* Index. The data sources are summarized in TABLE 1. Let r^{SP} and r^{vw} denote the market returns using *S&P* Composite Index and value weighted CRSP Index respectively. Market excess return is denoted by ($r^{SP} - r^{f}$) where r^{f} is the risk-free rate or the return on the 1-month Treasury bill.

Some of the most successful in-sample predictors that we are going to compare with mean deviations from debt service ratio (*DSR*) and financial obligations ratio (*FOR*) are as follows. The dividend price ratio (*d/p*) is the ratio of divided per share over price. The Dividend Yield (*d/y*) is the ratio of dividends over lagged prices. d/p and d/y have been studied in many articles. Ball (1978), Campbell (1987), Campbell and Shiller (1988a, 1988b), Campbell and Viceira (2002), Campbell and Yogo (2006), the survey in Cochrane (1997), Fama and French (1988), Hodrick (1992), Lewellen (2004), Menzly, Santos, and Veronesi (2004), Rozeff (1984), and Shiller (1984).

The Earnings Price Ratio (*e/p*) is the ratio of earnings over prices. I will also consider a successful corporate issuing activity variable, namely percent equity issuing (*eqis*), which is the ratio of equity issuing activity as a fraction of total issuing activity. This variable was proposed in Baker and Wurgler (2000). Another variable (*MKV/GDP)* is the ratio of market value to the GDP. In the TABLE 1 (*i/k*) is the investment to capital ratio which is the ratio of aggregate (private nonresidential fixed) investment to aggregate capital for the whole economy. This is the variable proposed in Cochrane (1991). Finally (*cay*) is the Consumption, wealth, income ratio proposed in Lettau and Ludvigson (2001).

TABLE 1
DATA SOURCE 1980-2015

Variables	Data source
r^{SP}, r^{vw}, r^{f}	CRSP : Center for Research in Security Prices
d/p, d/y, e/p	The $S\&P$ Corporation
cay	Sdyney Ludvigson's website
$eqis$, i/k	Amit Goyal's website
DSR, FOR, MKV/GDP	Federal Reserve Bank of St. Louis

The properties of all the above variables are very well known. Hence, in this paper, I will focus my attention on debt service ratio (*DSR*) and financial obligation ratio (*FOR*). TABLE 2 presents summary statistics for these variables using annual data between 1980 to 2015. TABLE 3 does the same job using quarterly data between 1980Q1-2015Q4.

TABLE 2
SUMMARY STATISTICS (ANNUAL DATA 1980-2015)

	r_t^{sp}	$r_t^{sp} - r_t^f$	DSR_t	FOR_t
Panel A : Correlation Matrix				
r_t^{sp}	1.00	0.977	-0.274	-0.221
$r_t^{sp} - r_t^f$		1.00	-0.246	-0.187
DSR_t			1.00	0.967
FOR_t				1.00
Panel B: Univariate Summary Statistics				
Mean	0.126	0.083	0.113	0.164
Standard error	0.166	0.161	0.009	0.009
Autocorrelation	-0.012	-0.044	0.861	0.813

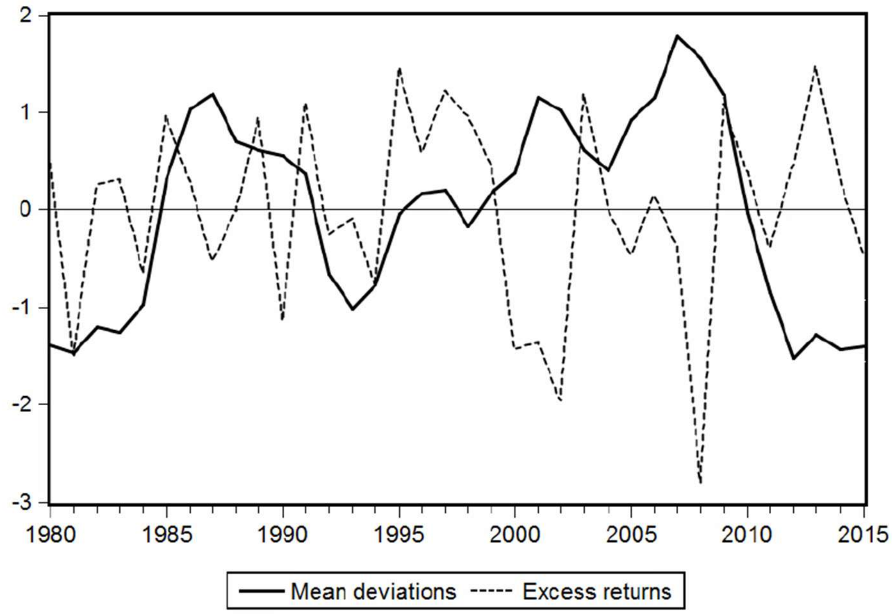
In both TABLE 2 and TABLE 3, DSR_t and FOR_t are negatively correlated with excess stock market returns. Mean of DSR_t and FOR_t are equal to 11.38% and 16.48% respectively with standard deviations close to 1 percent. Debt service ratio and financial obligation ratio are quite persistent, and the autocorrelation is high.

FIGURE 2 plots the standardized mean deviation of FOR_t and the standardized excess return on the *S&P* Composite Index over the period between 1980 and 2015. As discussed in previous section, large positive mean deviations preceded large negative excess returns and vice versa. This trend is quite perceptible during US recession periods, namely between 1990-07-01 to 1991-03-01, 2001-03-01 to 2001-11-01 and 2007-12-01, 2009-06-01. These are the NBER recession data between 1981 and 2015.

TABLE 3
SUMMARY STATISTICS (QUARTERLY DATA 1980Q1-2015Q4)

	r_t^{sp}	$r_t^{sp} - r_t^f$	DSR_t	FOR_t
Panel A : Correlation Matrix				
r_t^{sp}	1.00	0.993	-0.182	-0.151
$r_t^{sp} - r_t^f$		1.00	-0.169	-0.135
DSR_t			1.00	0.966
FOR_t				1.00
Panel B: Univariate Summary Statistics				
Mean	0.052	0.039	0.113	0.164
Standard error	0.082	0.081	0.009	0.008
Autocorrelation	0.100	0.077	0.978	0.966

FIGURE 2
EXCESS RETURNS AND MEAN DEVIATIONS FROM DSR



A detailed discussion on derivation of *DSR* and *FOR* is provided in appendix A. It is very important to check that mean deviations from obligation ratio is stationary over time because after all, expected returns appear to be stationary over time and the variables predicting these returns better be stationary as well. TABLE 4 shows the Augmented Dickey-Fuller (ADF) unit root test along with KPSS test to confirm this stationarity of the predicting variable.

TABLE 4
STATIONARITY TESTS FOR FINANCIAL OBLIGATION RATIO

ADF test statistic		prob.*	KPSS test statistic
	-3.522	0.014	**0.1492**
1 % level	-3.671		0.739
5 % level	-2.963		0.463
10 % level	-2.621		0.347

As ADF test statistic suggests, we can reject the null hypothesis at 1.5% significance level, meaning that we can reject if financial obligation ratio has a unit root property. KPSS test statistic also confirm the stationarity of this ratio as we could not reject the hypothesis that financial obligation ratio is stationary over time. The results hold for debt service ratio as well. Both ADF and KPSS tests for DSR confirms the stationarity of debt service ratio. This concludes the "Data and Summary Statistics" section.

FORECASTING REGRESSIONS

In this section, I am going to investigate the predictability power of mean deviations from households' obligation ratios for asset returns/ excess returns. The dependent variables are market returns ($S\&P_{500}$) and market excess returns. I also consider returns on the value weighted CRSP Index as it provides a better and broader proxy for total asset wealth than does the *S&P* Composite Index. The independent variable is the obligation ratio. For comparison purposes, I am going to assess the forecasting power of the most successful predicting variables using our sample data. These variables are the ones listed in TABLE 1, namely dividend price ratio (*d/p*), dividend yield ratio (*d/y*), earnings price ratio (*e/p*), percent equity issuing (*eqis*), investment to capital ratio (*i/k*), market to GDP ratio (*MKT/GDP*) and finally the consumption, wealth, income ratio (*cay*). TABLE 5 summarizes the regression results and report one-period-ahead forecasts of the stock market returns. We correct for generalized serial correlation of the residuals by using the Newey–West correction (Newey and West 1987) to the t-statistics.

The three panels in TABLE 5 summarize the results of OLS Single-regressions using *S&P* Composite Index returns, market excess returns and value-weighted market returns, respectively. As the table suggests, obligation ratio alone is significantly able to predict one-period ahead market returns. Note that the coefficients of *DSR* and *FOR* are both negative and significant at 1 percent level in all three panels. These negative coefficients are consistent with the economic intuition that we laid out in introduction section. As the economy is hit by a negative income shock, the increasing obligation ratio will be followed by lower expected returns. The R-squares are not worse than the ones generated by the most successful competitive predicting variables in the literature. Indeed, both obligation ratios have the highest R^2 among all after the *cay* variable. In next section I will show that obligation ratios are even better than *cay* when we do long run regressions.

In TABLE 5, Both the constants and coefficients of *DSR*, *FOR*, and *cay* are significant at 1 percent level in all 3 panels. Significant coefficients at 1 percent level are highlighted in bold face. The coefficient of dividend price ratio (*d/p*), earnings price ratio (*e/p*) and *MKV/GDP* are significant at 10 percent level in panel A and C. And the rest of the coefficients are not significant either using market returns or market excess returns.

To check the robustness of the results, as additional controls, TABLE 6 reports the regressions of market returns and market excess returns on variety of variables shown in the first row of the table. Panel A reports estimates from OLS multiple regressions of stock market returns on different combinations of the top row variables in the table. The highest adjusted R^2 is equal to 26.7% and belongs to row (4) where the right-hand side variables include debt service ratio, dividend price ratio and consumption wealth ratio.

TABLE 5
FORECASTING ONE-PERIOD AHEAD RETURNS (SINGLE REGRESSION)

	DSR	FOR	d/p	d/y	e/p	$eqis$	i/k	MKV/GDP	cay
Panel A: Market Returns (SP500)									
Constant	**0.124**	**0.123**	0.013	0.042	0.027	0.087	0.350	**0.185**	**0.100**
t-stat	6.719	5.862	0.158	0.577	0.391	1.593	0.916	6.535	3.522
Coefficient	**-5.380**	**-4.743**	4.101	2.757	1.633	0.230	-6.396	-0.052	**4.451**
t-stat	-3.362	-2.038	1.798	1.577	1.857	1.057	-0.555	-1.869	2.936
R^2	0.078	0.052	0.081	0.046	0.055	0.015	0.020	0.090	0.194
$adj.R^2$.	0.050	0.023	0.053	0.017	0.027	-0.015	-0.010	0.062	0.170
Panel B: Market Excess Returns									
Constant	**0.083**	**0.082**	0.021	0.053	0.036	0.074	0.418	**0.111**	**0.064**
t-stat	8.025	5.085	0.260	0.730	0.518	1.420	1.192	4.025	2.185
Coefficient	**-4.425**	-3.745	2.281	0.970	0.786	0.049	-9.452	-0.025	**3.668**
t-stat	-2.976	-1.741	1.039	0.551	0.890	0.224	-0.897	-0.880	2.306
R^2	0.054	0.033	0.026	0.006	0.013	0.001	0.044	0.021	0.136
$adj.R^2$.	0.026	0.004	-0.004	-0.024	-0.017	-0.030	0.015	-0.009	0.110
Panel C: Market Returns (CRSP_vw)									
Constant	**0.127**	**0.126**	0.014	0.044	0.027	0.087	0.341	**0.189**	**0.103**
t-stat	6.791	5.963	0.171	0.635	0.393	1.595	0.881	6.548	3.606
Coefficient	**-5.456**	**-4.845**	4.190	2.782	1.679	0.245	-6.063	-0.053	**4.482**
t-stat	-3.454	-2.103	1.925	1.685	1.905	1.115	-0.519	-1.889	2.965
R^2	0.078	0.053	0.083	0.046	0.057	0.016	0.017	0.090	0.193
$adj.R^2$.	0.050	0.025	0.055	0.017	0.029	-0.014	-0.013	0.063	0.169

However, in row (4) of TABLE 6, the constant is not significant! The only forecasting multiple regression in which all the coefficients are significant, and the constant is also significant at 1 percent level is the one where *DSR* and *cay* are the predictors, row (1) in panel A. Using these two variables alone generates an adjusted R^2 of 23.51% which is significantly higher that the R-squared estimated by using either *DSR* or *cay* individually.

In panel B, market excess returns are regressed on different variations of predictors. As in panel A, row (4) produces the highest adjusted R-squared but again the constant is not significant. Using *DSR* and *cay* alone will eventuate in an adjusted R^2 = 14.5% and significant coefficients and constant, row (1). In both panels, when we include all the predicting variables in row (7), debt service ratio and consumption wealth ratio are the only forecasting variables that remain significant in one-period-ahead multiple regressions. This reveals that *DSR* and *cay* contain information about future asset returns that is not included in other forecasting variables.

It is well known that some of these variables in top row of TABLE 6, typically perform better at forecast horizons more than two years. Thus, we also study the long run analysis and report the results in the long horizon forecast section of this paper. FIGURE 3, plots the normalized -standard deviations of unity- market excess returns (ERP) versus all the 9 variables listed in TABLE 5. The forecasting horizon *H* is equal to 1 in all graphs indicating that the regressions are the one-year-ahead forecasting regressions. The following TABLE 6 reports estimates from OLS multiple regressions of stock returns on variables named at the head of a column. The t-stats are Newey-West corrected ones. Regressions use data from 1980 to 2015. Number of stars above each variable indicate significance level. ***, ** and * are the 1,5, and 10 percent levels, respectively.

TABLE 6
FORECASTING ONE-PERIOD AHEAD RETURNS (MULTIPLE REGRESSIONS)

	constant	DSR	d/p	e/p	$eqis$	i/k	MKV/GDP	cay	R^2	$adj.R^2$.
Panel A: Additional Controls; Market Returns										
(1)	0.101***	-5.652**						4.543***	0.2801	0.2351
(2)	0.081	-5.249*	0.790					4.373***	0.2824	0.213
(3)	-0.044	-6.828***	2.815				0.053	5.784***	0.313	0.222
(4)	0.110	-7.078***	10.816***					4.772**	0.353	0.267
(5)	0.070	-4.893**	-0.269	0.657				4.519***	0.285	0.189
(6)	0.436*	-5.055*	-1.355	1.256	-0.115	-10.013		5.061**	0.333	0.191
(7)	0.218	-6.621**	1.136	1.359	-0.232	-7.259	0.049	6.175***	0.355	0.188
Panel B: Additional Controls; Excess Returns										
(1)	0.064**	-4.649*						3.744**	0.195	0.145
(2)	0.084	-5.045*	-0.776					3.911***	0.198	0.120
(3)	-0.106	-7.451**	2.308				0.082*	6.062**	0.273	0.176
(4)	0.119	-7.259***	11.361***					4.395**	0.305	0.212
(5)	0.084	-5.027*	-0.828	0.032				3.918***	0.198	0.091
(6)	0.566**	-5.201*	-2.364	0.836	-0.136	-13.206*		4.64**	0.283	0.129
(7)	0.241	-7.535***	1.348	0.989	-0.310	-9.103	0.074	6.307***	0.333	0.161

In FIGURE 3, we visualize the normalized (standard deviations of unity) market excess returns (ERP) versus all the 9 variables listed in TABLE 5. The forecasting horizon H is equal to 1 in all graphs indicating that the regressions are the one-year-ahead forecasting regressions. The R2 are also reported separately beneath each graph.

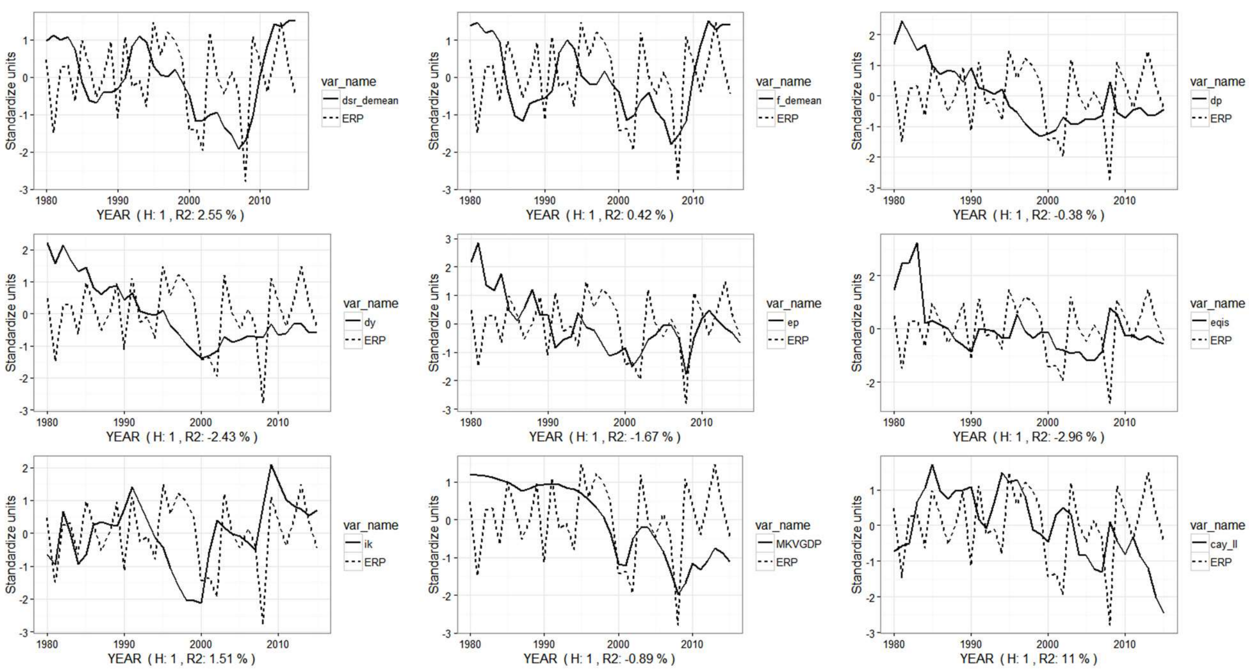
LONG HORIZON FORECASTS

In earlier sections, we showed that the household's obligation ratio is directly related to the interest rate. By construction, the higher the interest rate, the higher the household's financial obligations. This direct dependency suggests that, obligation ratio should track longer-term fluctuations in asset markets returns rather than providing accurate short-term forecasts. Furthermore, the summary statistics in TABLE 2 indicate that obligation ratios are highly persistent, supporting the idea that the obligation ratio should provide a more accurate signal of longer-term trends in asset returns than of short-term movements. This is like dividend price ratio and consumption wealth ratio which are both more accurate in predicting longer-term stock market returns.

TABLE 7 reports the results of single-regressions of H-period market returns and market excess returns on different lagged forecasting variables, over horizons spanning from 1 to 7 years. The table presents the estimated coefficient on the included explanatory variables, R^2 and the adjusted R^2, and the Newey-West corrected t-statistics. The significant coefficients at 5 percent level are highlighted in bold face.

In panel A, the H-period market returns are predicted by lagged values of forecasting variables listed in the column named “Regressors”. The predictive power of households’ obligation ratio (either *DSR* or *FOR*) is hump shaped and peaks around 6 periods with the adjusted R^2 of 27.9%. The coefficients remain almost constant and significant until the 6*th* period. This suggests that obligation ratio is relatively a stronger predictor in long horizons than other hump shaped variables like consumption wealth ratio (*cay*) which peaks around 2 periods. As expected, the dividend-price ratio, dividend-yield ratio and earnings-price ratio perform significantly better in longer horizons, however their predictability power in one-year-ahead forecasts are weak (not significant and with small adjusted R^2).

FIGURE 3
EXCESS RETURNS VERSUS PREDICTING FEATURES



Panel B in TABLE 7 reports the H-period forecasts using market excess returns. As this panel suggests, the obligation ratios are not as strong predictors as in panel A at very long horizons. The predictive power of obligation ratio peaks at 3 periods with adjusted R^2 equal to 12.30%. The coefficients are significant at 5 percent level until the 4*th* period. For consumption wealth ratio, the results are the same as in panel A. The predictive power peaks at second period and the coefficients are significant only up to this horizon with adjusted R^2 of 21.20%. For rest of the predicting variables, none of the coefficients are significant at 5 percent level over any horizon period between 1 to 7 years. In our sample, the only variable that provides significant predictability power for excess returns in longer horizons is the investment-capital ratio.

How robust are the results? As in short-horizon forecasts, we consider additional controls by including other predicting variables in the long-horizon regressions. We regress market returns and market excess returns on a list of variables including household obligation ratio (*DSR*), dividend-price ratio (*d/p*), earnings-price ratio (*e/p*), percent equity issuing (*eqis*), investment-capital ratio (*i/k*), market value to GDP (*MKV/GDP*) and finally consumption-wealth ratio (*cay*). TABLE 8 reports the long run multiple-regression estimates. The table reports estimate from OLS multiple regressions of stock returns on variables in the column named “Regressors”. The t-stats are Newey-West corrected ones and number of stars above each variable indicate significance level. As TABLE 8 suggests, in both panels, when including all the forecasting variables together, the household obligation ratio (*DSR*) in the **only** predicting variables which remains significant in all horizons spanning from 1 to 7 periods. While some variables are significant at shorter horizons, like *cay*, others are significant at longer horizons, like *d/p, e/p, eqis* and *i/k*. As in short-horizon regressions, this significancy of debt service ratio in all horizons reveals that DSR contain information about future asset returns that is not included in other forecasting variables.

FIGURE 4 plots the 5-year market excess returns versus lagged debt service ratio mean deviations. Note that in this figure, the *DSR* mean deviations has been flipped because *DSR*'s coefficient is expectedly negative in long horizon regressions. This figure shows how successful is the household's debt service ratio in predicting market excess returns over 5-year horizon. Finally, to see how obligation ratio performs relative to other variables in term of predicting long-horizon average returns, FIGURE 5 plots the normalized market returns (SP500) versus all the 9 variables listed in TABLE 7. The forecasting horizon *H* is equal to 5 in all graphs indicating that the regressions are the five-year-ahead forecasting regressions.

TABLE 8 reports estimated coefficients from OLS multiple regressions of stock returns on variables listed in the "Regressors" column. The t-stats are Newey-West corrected ones. Regressions use data from 1980 to 2015. Number of stars above each variable indicate significance level. ***, ** and * are the 1,5, and 10 percent levels, respectively.

TABLE 7
LONG-HORIZON FORECASTS (SINGLE REGRESSION)
ANNUAL DATA: 1980-2015

Row	Regressors		Forecast Horizon H 1	2	3	4	5	6	7
Panel A : Stock Market Returns									
		coefficient	**-5.380**	**-5.712**	**-5.932**	**-5.557**	**-5.271**	-4.567	-3.939
1	DSR	t-statistics	-3.362	-5.501	-3.466	-3.476	-2.767	-1.831	-0.994
		$adj.R^2$	0.050	0.135	0.223	0.235	0.261	0.279	0.240
		coefficient	**-4.743**	**-4.905**	**-5.067**	**-4.576**	**-4.525**	-3.973	-3.477
2	FOR	t-statistics	-2.038	-3.020	-2.945	-2.578	-2.369	-1.739	-1.471
		$adj.R^2$	0.023	0.076	0.132	0.126	0.156	0.172	0.150
		coefficient	4.101	**4.112**	3.910	**4.045**	**4.300**	**4.031**	**3.979**
3	d/p	t-statistics	1.798	2.367	1.714	2.180	3.237	3.550	5.659
		$adj.R^2$	0.053	0.134	0.194	0.282	0.417	0.517	0.611
		coefficient	2.757	**3.071**	**3.268**	**3.278**	**3.217**	**3.257**	**3.218**
4	d/y	t-statistics	1.577	1.936	1.979	2.398	3.664	4.265	5.507
		$adj.R^2$	0.017	0.085	0.169	0.232	0.287	0.426	0.509
		coefficient	1.633	**1.521**	**1.544**	**1.417**	**1.285**	1.105	1.211
5	e/p	t-statistics	1.857	2.399	2.307	2.415	2.519	1.771	1.249
		$adj.R^2$	0.027	0.067	0.123	0.138	0.145	0.153	0.236
		coefficient	0.230	0.327	0.341	0.341	**0.330**	0.310	**0.264**
6	$eqis$	t-statistics	1.057	1.745	1.745	1.911	2.092	1.720	1.969
		$adj.R^2$	-0.015	0.029	0.069	0.099	0.123	0.161	0.136

		coefficient	-6.396	-7.603	-9.457	-10.435	**-10.039**	**-9.974**	**-11.619**
7	i/k	t-statistics	-0.555	-0.671	-1.033	-1.873	-2.583	-3.009	-4.167
		$adj.R^2$	-0.010	0.025	0.099	0.172	0.199	0.260	0.360
		coefficient	-0.052	-0.047	-0.042	-0.039	-0.039	-0.039	-0.046
8	MKV/GDP	t-statistics	-1.869	-1.777	-1.424	-1.370	-1.432	-1.203	-1.515
		$adj.R^2$	0.062	0.117	0.144	0.160	0.196	0.271	0.401
		coefficient	**4.451**	**4.389**	**3.647**	**3.190**	**2.288**	**1.662**	1.282
9	cay	t-statistics	2.963	2.761	2.284	2.404	2.098	2.989	1.398
		$adj.R^2$	0.170	0.298	0.291	0.275	0.166	0.107	0.064

			Forecast Horizon H						
Row	Regressors		1	2	3	4	5	6	7
			Panel B : Market Excess Returns						
		coefficient	**-4.425**	**-4.435**	**-4.336**	-3.546	-2.983	-2.200	-1.645
1	DSR	t-statistics	-2.976	-4.496	-2.149	-1.806	-1.279	-0.752	-0.277
		$adj.R^2$	0.026	0.079	0.123	0.097	0.087	0.066	0.034
		coefficient	-3.745	**-3.631**	-3.530	-2.607	-2.272	-1.639	-1.236
2	FOR	t-statistics	-1.741	-2.581	-1.839	-1.543	-1.085	-0.631	-0.535
		$adj.R^2$	0.004	0.033	0.059	0.028	0.027	0.014	-0.002
		coefficient	2.281	2.376	2.228	2.403	2.713	2.503	**2.497**
3	d/p	t-statistics	1.039	1.357	0.898	1.124	1.876	1.836	3.131
		$adj.R^2$	-0.004	0.029	0.051	0.100	0.196	0.262	0.338
		coefficient	0.970	1.392	1.627	1.693	1.695	1.798	1.798
4	d/y	t-statistics	0.551	0.860	0.853	1.040	1.599	1.686	1.805
		$adj.R^2$	-0.024	-0.005	0.025	0.051	0.080	0.161	0.214
		coefficient	0.786	0.750	0.826	0.726	0.594	0.419	0.551
5	e/p	t-statistics	0.890	1.167	1.158	1.136	1.044	0.575	0.441
		$adj.R^2$	-0.017	-0.005	0.018	0.021	0.015	0.002	0.046
		coefficient	0.049	0.154	0.175	0.185	0.180	0.162	0.105
6	$eqis$	t-statistics	0.224	0.814	0.944	1.068	1.396	1.243	1.058
		$adj.R^2$	-0.030	-0.016	-0.002	0.013	0.025	0.039	0.003
		coefficient	-9.452	-10.034	-11.301	**-11.803**	**-10.968**	**-10.302**	**-10.947**
7	i/k	t-statistics	-0.897	-1.123	-1.706	-3.352	-5.528	-6.033	-4.905
		$adj.R^2$	0.015	0.077	0.182	0.282	0.323	0.405	0.481

		coefficient	-0.025	-0.020	-0.016	-0.014	-0.015	-0.017	-0.023
8	MKV/GDP	t-statistics	-0.880	-0.714	-0.500	-0.463	-0.547	-0.453	-0.559
		$adj.R^2$	-0.009	-0.001	-0.003	-0.002	0.011	0.041	0.127
		coefficient	**3.668**	**3.599**	2.843	2.378	1.506	0.989	0.734
9	cay	t-statistics	2.306	2.096	1.521	1.611	1.220	1.618	0.922
		$adj.R^2$	0.110	0.212	0.191	0.172	0.077	0.035	0.012

QUARTERLY DATA: 1980Q1-2015Q4

			Forecast Horizon H							
Row	Regressors		1	2	4	8	12	24	36	48
			Panel A: Stock Market Returns							
		coefficient	**-1.805**	-1.753	-1.876	-1.987	**-2.027**	**-1.690**	-1.188	-0.842
1	DSR	t-stat	-1.978	-1.764	-1.127	-1.701	-2.533	-3.061	-1.473	-0.819
		asj. R^2	0.029	0.054	0.123	0.251	0.331	0.389	0.210	0.103
		coefficient	-1.678	-1.613	-1.766	-1.866	**-1.898**	**-1.629**	-1.121	-0.781
2	FOR	t-stat	-1.696	-1.619	-1.006	-1.877	-2.704	-2.681	-1.068	-0.607
		asj. R^2	0.020	0.038	0.094	0.193	0.257	0.319	0.171	0.100
		coefficient	**2.050**	**2.040**	**1.871**	1.692	**1.700**	**1.557**	**1.324**	**1.136**
3	d/p	t-stat	3.136	3.057	2.094	1.791	2.169	5.322	5.815	4.875
		asj. R^2	0.080	0.150	0.247	0.384	0.522	0.824	0.867	0.817
		coefficient	**2.077**	**1.982**	**1.754**	**1.588**	**1.633**	**1.476**	**1.280**	**1.093**
4	d/y	t-stat	3.456	3.362	2.240	2.067	3.212	8.781	8.171	6.494
		asj. R^2	0.087	0.149	0.228	0.356	0.510	0.784	0.855	0.798
		coefficient	**0.866**	**0.814**	0.733	**0.613**	**0.629**	0.512	**0.544**	**0.458**
5	e/p	t-stat	2.272	2.044	1.626	2.393	2.455	1.936	2.986	3.021
		asj. R^2	0.067	0.112	0.179	0.240	0.346	0.446	0.670	0.664
		coefficient	-1.515	-1.655	-1.828	-2.317	-2.726	-2.809	**-2.860**	-2.090
6	i/k	t-stat	-0.805	-0.751	-0.709	-0.482	-0.866	-0.935	-1.995	-0.857
		asj. R^2	-0.003	0.003	0.015	0.061	0.119	0.202	0.262	0.192
		coefficient	**0.747**	**0.810**	**0.917**	1.030	0.895	0.380	0.226	0.109
7	cay	t-stat	2.568	2.867	2.367	1.880	1.534	1.128	0.548	0.234
		asj. R^2	0.020	0.050	0.120	0.257	0.244	0.070	0.025	-0.003

Row	Regressors		Forecast Horizon H 1	2	4	8	12	24	36	48
			Panel B: Market Excess Returns							
		coefficient	-1.637	-1.559	-1.634	-1.657	**-1.616**	-1.100	-0.657	-0.434
1	DSR	t-stat	-1.845	-1.726	-1.048	-1.650	-2.811	-1.693	-1.079	-0.644
		asj. R^2	0.023	0.043	0.099	0.200	0.259	0.243	0.099	0.040
		coefficient	-1.481	-1.386	-1.491	-1.514	**-1.481**	-1.040	-0.626	-0.431
2	FOR	t-stat	-1.606	-1.435	-0.854	-1.604	-2.712	-1.652	-1.000	-0.533
		asj. R^2	0.014	0.027	0.070	0.145	0.192	0.191	0.082	0.045
		coefficient	**1.522**	**1.513**	1.355	1.211	1.251	**1.169**	**0.964**	0.820
3	d/p	t-stat	2.193	2.062	1.354	1.184	1.316	4.233	3.170	1.931
		asj. R^2	0.042	0.082	0.135	0.224	0.349	0.692	0.746	0.712
		coefficient	**1.558**	**1.461**	1.243	1.111	**1.187**	**1.090**	**0.928**	**0.783**
4	d/y	t-stat	2.374	2.204	1.373	1.288	2.037	5.564	4.624	3.748
		asj. R^2	0.047	0.081	0.119	0.198	0.332	0.637	0.729	0.685
		coefficient	0.628	0.575	0.498	0.398	0.434	0.340	**0.395**	**0.321**
5	e/p	t-stat	1.595	1.273	1.019	1.443	1.554	1.382	2.446	1.875
		asj. R^2	0.033	0.055	0.085	0.113	0.202	0.291	0.574	0.545
		coefficient	-2.508	-2.623	-2.719	-3.028	-3.257	-2.853	-2.612	-1.773
6	i/k	t-stat	-1.349	-1.231	-1.142	-0.754	-1.222	-3.009	-2.177	-1.060
		asj. R^2	0.005	0.018	0.047	0.128	0.217	0.315	0.358	0.234
		coefficient	0.584	**0.651**	0.762	0.888	0.758	0.249	0.165	0.119
7	cay	t-stat	1.986	2.177	1.914	1.669	1.359	0.996	0.505	0.348
		asj. R^2	0.010	0.031	0.087	0.219	0.217	0.042	0.021	0.005

FIGURE 4
DEBT SERVICE RATIO: 1980-2015 FOLLOWING 5-YEAR EXCESS RETURNS

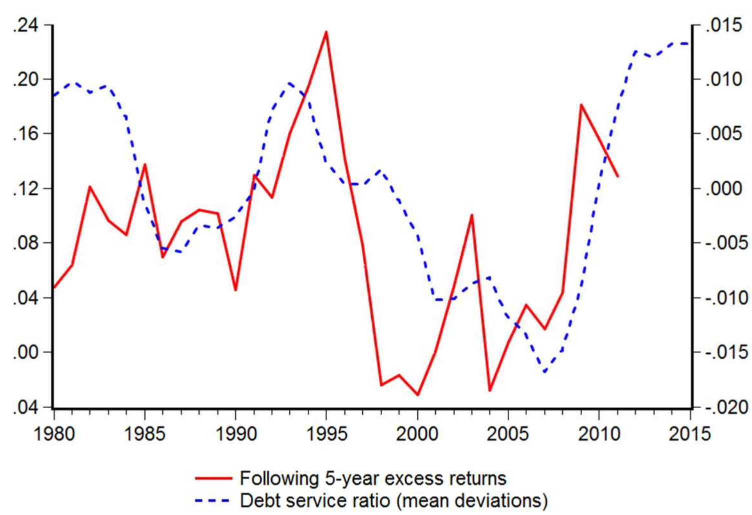


FIGURE 5
EXCESS RETURNS VERSUS H-HORIZON PREDICTING FEATURES

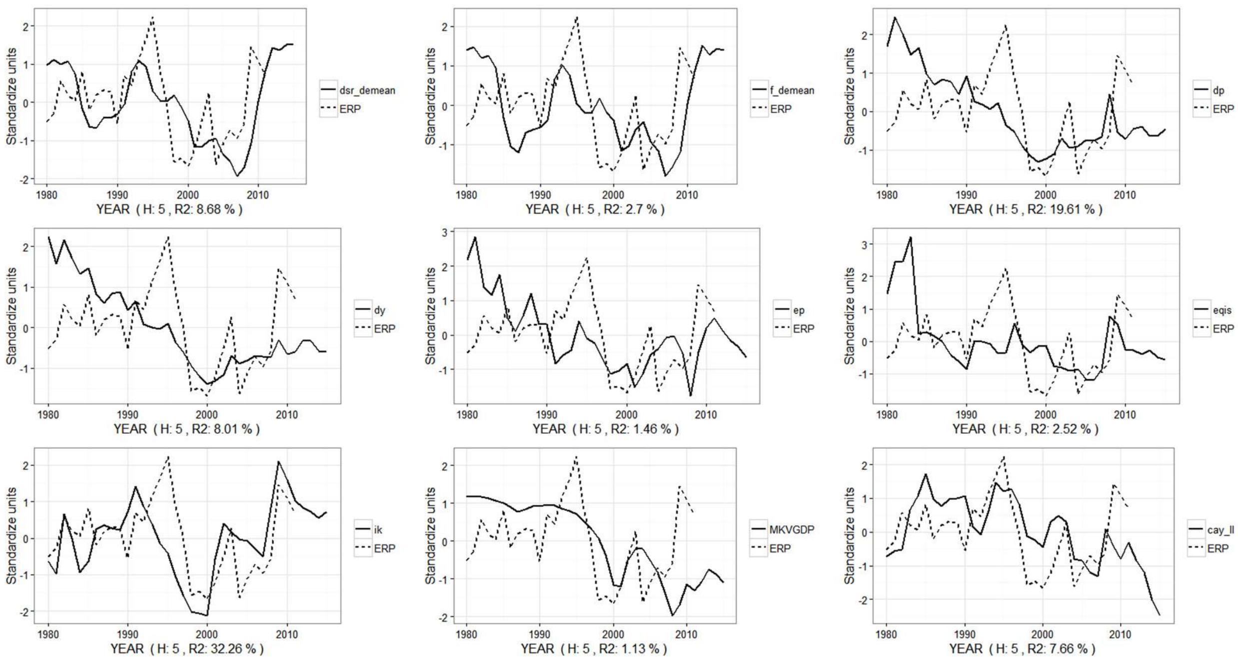


TABLE 8
FORECASTING H-PERIOD AHEAD RETURNS (MULTIPLE REGRESSIONS)

Regressors	Forecast Horizon H 1	2	3	4	5	6	7
	Panel A: Additional Controls; Market Returns						
constant	0.219	0.281	0.392**	0.367***	0.267***	0.302***	0.275***
DSR	-6.622**	-4.834***	-3.953***	-4.433**	-7.889***	-6.602***	-3.839***
d/p	1.136	0.025	-1.258	1.311	6.008***	5.819***	5.549***
e/p	1.360	1.261	1.473	0.666	-0.554	-0.975***	-0.897**
$eqis$	-0.232	0.043	0.135	0.010	-0.342**	-0.301**	-0.290***
i/k	-7.260	-8.790	-11.052**	-10.361***	-7.733***	-7.228***	-5.727***
MKV/GDP	0.050	0.040	0.026*	0.031***	0.053***	0.032**	0.006
cay	6.176***	5.700***	4.571***	3.461**	1.807**	0.552	-0.117
Adjusted R^2	0.188	0.468	0.630	0.697	0.778	0.839	0.835
	Panel B: Additional Controls; Market Excess Returns						
constant	0.242	0.280	0.379**	0.361***	0.268***	0.302***	0.278***
DSR	-7.536***	-5.642***	-4.588***	-4.884***	-7.987***	-6.258***	-3.446***
d/p	1.348	0.235	-1.180	1.098	5.524***	5.215***	4.807***
e/p	0.990	1.005	1.309	0.575	-0.579*	-0.992***	-0.841**
$eqis$	-0.311	-0.042	0.055	-0.053	-0.386***	-0.327***	-0.314***
i/k	-9.104	-10.099	-12.017***	-11.320***	-8.729***	-8.061***	-6.680***
MKV/GDP	0.074	0.065**	0.050***	0.051***	0.070***	0.045***	0.019
cay	6.307***	5.790***	4.579***	3.355***	1.657**	0.425***	-0.144
Adjusted R^2	0.161	0.444	0.596	0.648	0.726	0.750	0.688

OUT-OF-SAMPLE TESTS

In this section, we study the out-of-sample performance of household obligation ratio by comparing the mean-squared error from one-period-ahead out-of-sample forecasts obtained from a forecasting regression that includes household obligation ratio as the only forecasting variable, to a variety of forecasting regressions that do not include it.

We need to choose the periods over which a regression model is estimated and subsequently evaluated. Although any choice is necessarily ad-hoc in the end, the criteria are clear. It is important to have enough initial data to get a reliable regression estimate at the start of evaluation period, and it is important to have an evaluation period that is long enough to be representative. Since our annual data is limited, we investigate quarterly periods as well. More specifically, we use one-third of the data to estimate the regression models and the rest of the data to report out-of-sample results. We consider a benchmark models and compare it with the out of sample performance of obligation ratios, then we do some non-nested analysis comparing the performance of debt service ratio with other predicting variable mentioned earlier in this paper. The benchmark model is the historical mean benchmark.

In historical mean benchmark, a constant is the sole explanatory variable for excess returns. It has been documented (Welch and Goyal 2008) that most of the predicting variables in the literature have no ability to predict out-of-sample returns relative to a historical mean model despite their ability to do so in-sample. Hence, in this paper, we will also produce Goyal-Welch type figures to see the out-of-sample performance of obligation ratio relative to historical mean models.

Out-of-Sample Empirical Procedure

I will closely follow Welch and Goyal 2008 empirical procedure. The OOS forecast uses only the data available up to the time at which the forecast is made. Let e_B denote the vector of expanding OOS errors from the benchmark model and e_A denote the vector of expanding OOS errors from the OLS conditional model. The OOS statistics are:

$$R^2 = 1 - \frac{MSE_A}{MSE_B} \tag{1}$$

$$\Delta RMSE = \sqrt{MSE_B} - \sqrt{MSE_A} \tag{2}$$

$$MSE_F = (T - h + 1)\left(\frac{MSE_B - MSE_A}{MSE_A}\right) \tag{3}$$

R^2 is the out-of-sample R-squared (OOS-R^2). $MSE_A = E[e^2_A]$ is the mean squared forecasting error from the relevant conditional model. $MSE_B = E[e^2_B]$ is the mean squared error from the benchmark model. $RMSE$ is the root mean square error and $\Delta RMSE$ is the difference between the benchmark forecast and the conditional forecast for the same sample/forecast period. Positive numbers for $\Delta RMSE$ indicate superior out-of-sample conditional forecast. MSE_F is a test statistic designed to determine whether the one-step-ahead forecasting performance from the benchmark model is statistically different from the conditional model. It is an out-of-sample F-type test developed in McCracken (2004). h is the degree of overlap. The MSE_F test is a test of equal mean-squared forecasting error. The null hypothesis is that the conditional model (model-1) and the benchmark models (model-2) have equal mean-squared error, the alternative hypothesis is that the benchmark model (model-2) has higher MSE than conditional model (model-1). When we compare obligation ratio models with other conditional models, the debt service ratio model will be the model-1 and each of the other predicting variable models will be model-2 separately.

We compare out-of-sample performance of obligation ratio with other conditional models by providing figures like the ones in Welch and Goyal 2008. These figures plot the IS and OOS performance of conditional models.

"For the IS regressions, the performance is the cumulative squared demeaned returns minus the cumulative squared regression residual. For the OOS regressions, this is the cumulative squared prediction errors of the prevailing mean minus the cumulative squared prediction error of the predictive variable from the linear historical regression. In the figures, whenever a line increases, the conditional model predicted better; whenever it decreases, the historical mean model predicted better. The units in the graphs are not intuitive, but the time series pattern allows diagnosis of years with good or bad performance. Indeed, the final ΔSSE statistic in the OOS plot is sign-identical with the $\Delta RMSE$ statistic in my tables. In these figures, we can easily adjust perspective to see how variations in starting or ending date would impact the conclusion by shifting the graph up or down (redrawing the y = 0 horizontal zero line). The plots have also vertically shifted the IS errors, so that the IS line begins at zero on the date of our first OOS prediction" (Welch and Goyal 2008).

TABLE 9 summarizes the out-of-sample results. The upper tabular uses annual data, the initial estimation period begins with 1980 and ends with 2000. The OOS estimation period is equal to 20 which is equal to the number that Welch and Goyal used in their tables. The model is recursively re-estimated until up to 2015. Out of sample tests are performed for three different overlapping horizons. We consider two-year and three-year overlapping horizons to capture the business cycles fluctuations. The lower tabular of TABLE 9 does the same job using quarterly data. The OOS estimation period here is equal to 48 which is one third of the number of periods in the full sample. In this tabular, we report OOS results for one-quarter, four-quarter and eight-quarter overlapping horizons.

As TABLE 9 reports, the mean-squared forecasting error of the household obligation ratio model (either DSR or FOR) is always lower than that of the historical mean benchmark model except for one single column where OOS market excess returns are predicted using one-year returns (H = 1). The MSE-F tests are not significant when using annual data and H=1, this is somewhat expected as the number of out of sample periods and the valuation periods do not seem to be sufficiently large. In the lower tabular of TABLE 9, when we use quarterly data, the OOS-R2 is always positive and the MSE-F statistic strongly reject the null hypothesis. This suggests that information on the aggregate household's obligation ratio consistently improve forecasts over models that used only a constant as a predictive variable.

TABLE 9
OUT-OF-SAMPLE TESTS
ANNUAL DATA: 1980-2015, OOS ESTIMATION PERIOD=20

	H=1		H=2		H=3	
	DSR	FOR	DSR	FOR	DSR	FOR
Panel A: Stock Market Returns						
IS R^2	0.050	0.023	0.135	0.076	0.223	0.132
OOS R^2	0.019	0.015	0.143	0.095	0.293	0.196
$\Delta RMSE$	0.002	0.001	0.011	0.007	0.019	0.013
MSE-F	0.310	0.239	2.329	1.468	4.969	2.932
Panel B: Market Excess Returns						
IS R^2	0.026	0.004	0.079	0.033	0.123	0.059
OOS R^2	-0.040	-0.043	0.061	0.026	0.158	0.093
$\Delta RMSE$	-0.004	-0.004	0.004	0.002	0.009	0.005
MSE-F	-0.617	-0.662	0.917	0.377	2.246	1.237

QUARTERLY DATA: 1980Q1-2015Q4, OOS ESTIMATION PERIOD=48

	H=1		H=4		H=8	
	DSR	FOR	DSR	FOR	DSR	FOR
Panel A: Stock Market Returns						
IS R^2	0.029	0.020	0.123	0.094	0.251	0.193
OOS R^2	0.029	0.022	0.156	0.122	0.249	0.189
$\Delta RMSE$	0.001	0.001	0.004	0.003	0.005	0.004
MSE-F	2.886	2.191	16.620	12.492	27.165	19.067
Panel B: Market Excess Returns						
IS R^2	0.023	0.014	0.099	0.070	0.200	0.145
OOS R^2	0.023	0.017	0.131	0.096	0.212	0.154
$\Delta RMSE$	0.001	0.001	0.003	0.002	0.004	0.003
MSE-F	2.295	1.637	13.540	9.603	21.998	14.905

From TABLE 9, as we expand the number of overlapping horizons, both IS and OOS R^2 increase and MSE-F statistics become stronger. This is consistent with what we found in the long-horizon analysis in previous section.

TABLE 10 compares statistics on OOS performance of debt service ratio versus other conditional models using different predicting variables, namely *d/p*, *d/y*, *e/p*, *i/k*, *eqis*, *MKV/GDP* and *cay*. We don't have quarterly data for *eqis* and *MKV/GDP* so we exclude these variables when reporting results using quarterly data (lower tabular of TABLE10).

TABLE 10
OUT-OF-SAMPLE TESTS

ANNUAL DATA

	H=1		H=2		H=3	
	MSE1/MSE2	MSE-F	MSE1/MSE2	MSE-F	MSE1/MSE2	MSE-F
Panel A: Stock Market Returns						
DSR vs. d/p	1.052	-0.794	0.980	0.286	0.920	1.046
DSR vs. d/y	0.928	1.244	0.873	2.042	0.867	1.849
DSR vs. e/p	1.039	-0.599	0.926	1.118	0.838	2.321
DSR vs. $eqis$	0.983	0.276	0.904	1.491	0.805	2.901
DSR vs. i/k	0.927	1.267	0.804	3.422	0.774	3.495
DSR vs. MKV/GDP	0.800	4.001	0.769	4.197	0.674	5.803
DSR vs. cay	1.198	-2.649	1.195	-2.287	1.044	-0.509
Panel B: Market Excess Returns						
DSR vs. d/p	0.980	0.329	0.896	1.627	0.850	2.117
DSR vs. d/y	0.865	2.504	0.804	3.404	0.791	3.169
DSR vs. e/p	1.002	-0.035	0.907	1.430	0.848	2.154
DSR vs. $eqis$	0.974	0.419	0.908	1.411	0.847	2.164
DSR vs. i/k	1.003	-0.046	0.947	0.786	1.079	-0.882
DSR vs. MKV/GDP	0.721	6.183	0.691	6.250	0.636	6.872
DSR vs. cay	1.104	-1.511	1.068	-0.894	0.953	0.587

QUARTERLY DATA

	H=1		H=4		H=8	
	MSE1/MSE2	MSE-F	MSE1/MSE2	MSE-F	MSE1/MSE2	MSE-F
Panel A: Stock Market Returns						
DSR vs. d/p	1.044	-4.085	1.113	-9.148	1.198	-13.549
DSR vs. d/y	1.049	-4.475	1.119	-9.575	1.183	-12.700
DSR vs. e/p	1.046	-4.192	1.033	-2.896	0.975	2.083
DSR vs. i/k	0.950	5.056	0.837	17.568	0.759	26.037
DSR vs. cay	0.998	0.188	1.013	-1.166	1.052	-4.086
Panel B: Market Excess Returns						
DSR vs. d/p	1.003	-0.291	0.991	0.815	1.008	-0.626
DSR vs. d/y	1.004	-0.388	0.994	0.546	0.992	0.686
DSR vs. e/p	1.008	-0.767	0.951	4.679	0.886	10.579
DSR vs. i/k	0.968	3.213	0.909	9.028	0.878	11.432
DSR vs. cay	0.987	1.296	0.984	1.505	1.036	-2.872

The comparison is done using stock market returns (Panel A) and market excess returns (Panel B) forecasts at annual frequency (upper tabular) and quarterly frequency (lower tabular). The ratio of mean square errors MSE1/MSE2 smaller than one indicates that the mean-squared forecasting error of the *DSR* is lower than that of the competitor conditional model. Annual data tabular and quarterly data tabular both suggest that for the cases in which MSE-F is significant, the DSR forecasting model contains information that produces (almost always) superior forecasts to those produced by any of the competitor models. For longer overlapping horizons, this is always the case, suggesting that forecasts using obligation ratio presented here would be consistently superior to forecasts using other popular forecasting variables whenever we can support the accuracy of the tests.

FIGURE 6 graphs the IS and OOS performance of the debt service ratio augmented model using annual data (the three graphs on the left) and quarterly data (the graphs on the right) for different overlapping horizons. For the IS regressions, the performance is the cumulative squared demeaned returns minus the cumulative squared regression residual. For the OOS regressions, this is the cumulative squared prediction errors of the prevailing mean minus the cumulative squared prediction error of the predictive variable from the linear historical regression.

In FIGURE 6, whenever a line increases, the DSR-augmented model predicted better; whenever it decreases, the historical mean model predicted better. The final ΔSSE statistic in the OOS plot is sign-identical with the ΔRMSE statistic in our tables. The figure adjusts perspective to see how variations in starting or ending date would impact the conclusion by shifting the graph up or down (redrawing the y = 0 horizontal zero line). The plots have also vertically shifted the IS errors, so that the IS line begins at zero on the date of our first OOS prediction (1980 for annual data and 19800 i.e., 1980Q1 for quarterly data).

As FIGURE 6 suggests, the performance of DSR-augmented model is consistent with what we found in TABLE 9. As we increase the number of overlapping horizons, the OOS performance become closer to IS performance. FIGURE 7 graphs the IS and OOS performance of each conditional model separately. The conditional model is a model that relies on predictive variables noted in each graph. The benchmark is the historical mean model. The interpretation of increase and decrease in lines are the same as in FIGURE 6.

In FIGURE 7, we only show the graphs using stock market annual returns (SP500), OOS estimation period equals to 20, and overlapping horizon equal to one (H=1). The OOS performance of each model is closer to its IS performance if the two solid and dashed lines are closer to each other. The figure suggests that obligation ratios, *cay*, *e/p* and *eqis* augmented models perform relatively better than the other conditional models.

FIGURE 6
OUT-OF-SAMPLE PERFORMANCE OF DSR-AUGMENTED MODEL

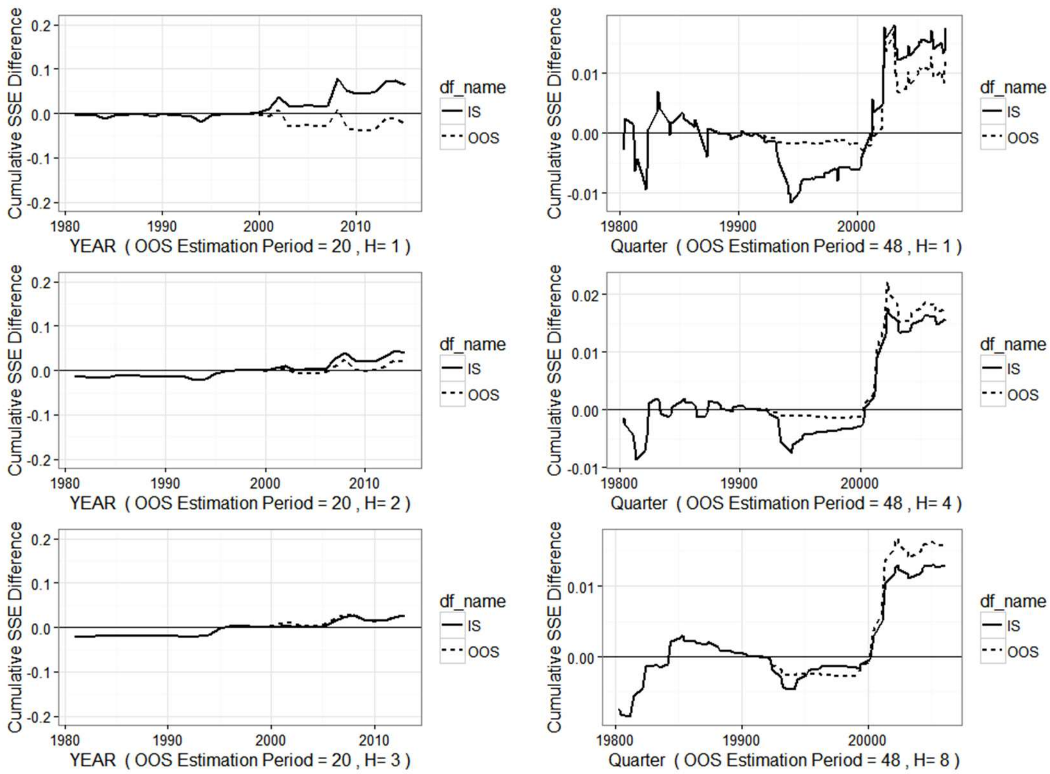
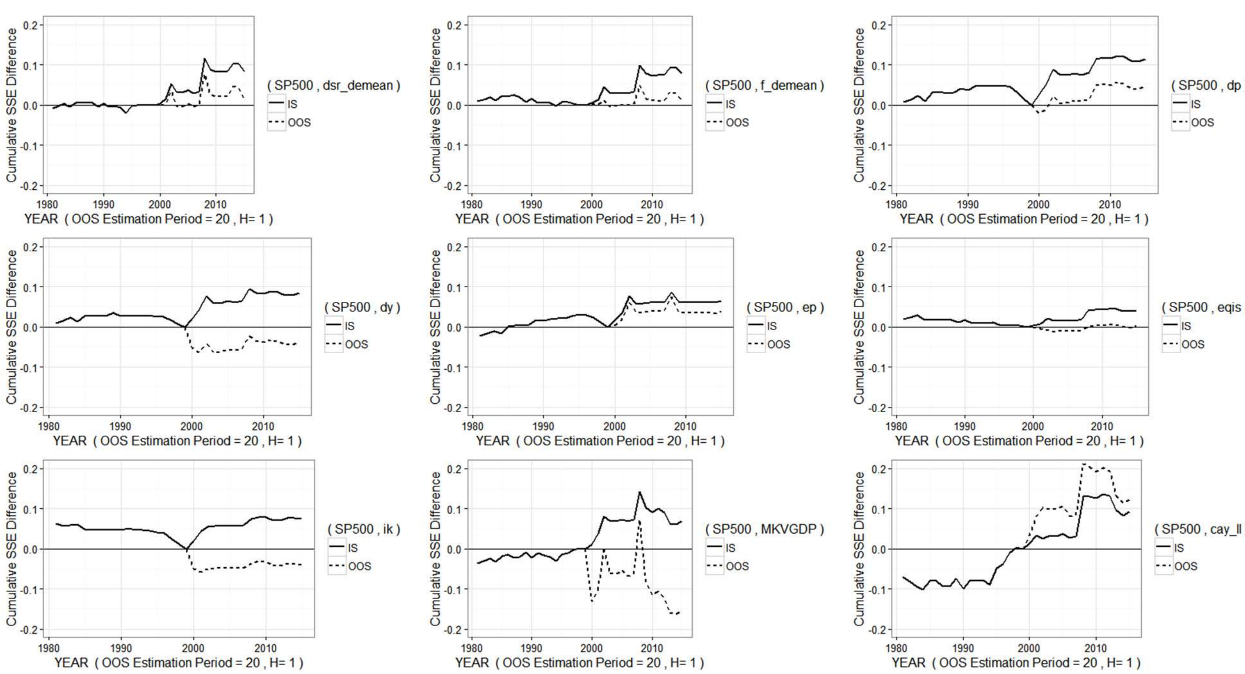


FIGURE 7
OUT-OF-SAMPLE PERFORMANCE OF CONDITIONAL MODELS



CONCLUSION

Using annual and quarterly data between 1980 and 2015, we show that household's obligation ratio can predict stock market returns at short horizon and over business cycle frequencies. Debt service ratio is a macroeconomic business cycle variable which is a better forecaster of future returns both in-sample and out-of-sample than dividend-price ratio, dividend yield, earnings-price ratio, investment-capital ratio, and several other popular forecasting variables. We use multiple regression analysis including some of the most successful predicting variables in the literature for forecasting one-period ahead returns and we find that debt service ratio and consumption wealth ratio are the only forecasting variables that remain significant in these regressions. This reveals that debt service ratio contains information about future asset returns that is not included in other forecasting variables. We also do out-of-sample tests and find that information on the aggregate household's obligation ratio consistently improve forecasts over models that use only a constant as a predictive variable and over other conditional models that use popular forecasting variables.

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APPENDIX A

From Federal Reserve's Board: The household Debt Service Ratio (DSR) is the ratio of total required household debt payments to total disposable income. The DSR is divided into two parts: Mortgage DSR and Consumer DSR. The Mortgage DSR is total quarterly required mortgage payments divided by total quarterly disposable personal income. The Consumer DSR is total quarterly scheduled consumer debt payments divided by total quarterly disposable personal income. The Mortgage DSR and the Consumer DSR sum to the DSR. Quarterly values for the Debt Service Ratio are available from 1980 forward.

The limitations of current sources of data make the calculation of the ratio especially difficult. The ideal data set for such a calculation would have the required payments on every loan held by every household in the United States. Such a data set is not available, and thus the calculated series is only an approximation of the debt service ratio faced by households. Nonetheless, this approximation is useful to the extent that, by using the same method and data series over time, it generates a time series that captures the important changes in the household debt service burden. The series are revised as better data or improved methods of estimation become available. To create the measure, payments are calculated separately for revolving debt and for each type of closed-end debt, and the sum of these payments is divided by disposable personal income as reported in the National Income and Product Accounts. For revolving debt, the assumed required minimum payment is 2-1/2 percent of the balance per month. This estimate is based on the January 1999 Senior Loan Officer Opinion Survey, in which most banks indicated that required monthly minimum payments on credit cards ranged between 2 percent and 3 percent, a ratio that apparently had not changed substantially over the previous decade.

Payments on closed-end loans, which are calculated for each major category of closed-end loan, are derived from the loan amount outstanding, the average interest rate, and the average remaining maturity on the stock of outstanding debt. Estimates of the amount of mortgage debt are taken from the Federal Reserve Board's Z.1 Financial Accounts of the United States statistical release and estimates of outstanding consumer debt are taken from the Federal Reserve's G.19 Consumer Credit statistical release. For consumer debt, a more detailed breakdown by type of closed-end loan is obtained using internal Federal Reserve estimates and data from the Federal Reserve's Survey of Consumer Finances (SCF). Interest rates on closed-end consumer loans are obtained from the Federal Reserve Board's G.19 Consumer Credit and G.20 Finance Companies statistical releases, the SCF, and additional proprietary data sources. An estimate of the interest rate on the stock of outstanding debt is obtained by weighting the recent history of interest rates using information on the age of outstanding loans in the SCF. The interest rate on the stock of outstanding mortgage debt is an estimate provided by the Bureau of Economic Analysis. Maturity series for consumer debt are taken from the SCF. Maturity series for mortgage debt are calculated using data from Lender Processing Services and Mortgage Bankers Association.

The financial obligations Ratio is a broader measure than the Debt Service Ratio. It includes rent payments on tenant-occupied property, auto lease payments, homeowners' insurance, and property tax payments. These statistics are obtained from the National Income and Product Accounts.