Davids, Goliaths, and Business Cycles

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Abstract

A long literature in financial economics implies that the relative performance of firms with worse access to external financing should forecast aggregate market returns and future real economic activity. We test this implication with a new variable GVD (Goliath versus David), which is the annual change in the weight of the largest firms in the aggregate stock market. We find that GVD is the best single predictor of market returns out-of-sample among nine traditional predictors, predicting quarterly market returns with an out-of-sample R^2 of 6.3% in the 1976-2011 evaluation period. Moreover, GVD is the only variable among traditional predictors that forecasts stock returns and investment growth both in-sample and out-of-sample. GVD also forecasts returns and investment growth of the Fama-French ten size-sorted portfolios, with assets we ex-ante expect to be more sensitive to changes in the access to external financing displaying greater sensitivity to GVD. GVD's predictive ability is robust, and not due to information contained in traditional variables, such as SMB and net payout. Overall, our findings imply that shocks to access to external financing often precede macroeconomic fluctuations suggesting that financial markets play an important role in real economic activity.

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The financial accelerator hypothesis (e.g. Bernanke and Gertler (1989), Bernanke, Gertler, and Gilchrist (1996), Kiyotaki and Moore (1997) and Perez-Quiros and Timmermann (2000)) highlights the role of financial markets in the magnification of aggregate economic shocks. The hypothesis states that following aggregate shocks, financially constrained firms find it harder to access external finance and therefore reduce investment. This results in a reduction in aggregate investment and thereby amplifies the original shock. A large body of research finds empirical support of this theory, typically using size as a measure of financial constraints. For example Gertler and Gilchrist (1994) find that small firms cut their investment more than large firms following macroeconomic shocks. Prior research however, has not examined whether the relative performance of firms with worse access to external finance forecasts aggregate economic activity. This is surprising because, according to the financial accelerator hypothesis, constrained firms are the quintessential "canary in the coal mine" and hence their relative performance should forecast aggregate economic activity and should also be correlated with aggregate risk premium. In this paper, we test these forecasting implications of the financial accelerator hypothesis.

We do so, by proposing a simple forecasting variable, Goliath Versus David (or GVD). GVD is the change in the weight of the stocks of the largest firms in the aggregate market portfolio over a 12-month period. Hence GVD is a measure of the valuation of the largest and least financially constrained firms relative to the entire market. An intuitive way to understand the strong connection between GVD and the literature on financial constraints is to notice that GVD has two components and each of these components is strongly related to the literature. The first component is the difference between the return on existing capital of the largest firms and the return on the market (GVD_{OLD}) and the second is the difference between the net new equity issuances of the largest firms and the net new equity issuance of the market (GVD_{NEW}).[1] GVD_{OLD} is strongly related to the work of Perez-Quiros and Timmermann (2000), who show that the expected return and risk of small firms exhibit greater increases than those of large firms during periods of economic stress. Therefore the results in Perez-Quiros and Timmermann (2000) imply that the realized returns of the largest firms in the market are larger than those of the smallest firms during periods of finan-

[1] Note that this decomposition also highlights the way in which GVD is distinct from the Fama and French (1993) factor, SMB, since SMB is only related to GVD_{OLD} and not to GVD_{NEW}.

cial distress and hence GVD_{OLD} increases during these periods. On the other hand, GVD_{NEW} is strongly related to Covas and Den Haan (2011), who find that small firms have much more cyclical equity issuance than do large firms. As a result, GVD_{NEW} also increases in periods of financial distress. GVD therefore combines the two consequences of aggregate economic shocks for small and large firms into a single, economically-intuitive and countercyclical variable.[2]

Once we build GVD, we examine five of the forecasting implications of the financial accelerator theory. First, the models in Bernanke and Gertler (1989) and Kiyotaki and Moore (1997) imply that the increase in the cost of external financing causes lower aggregate investment, hence increases in GVD should predict declines in aggregate investment. Second, the fact that smaller firms have larger expected returns and risk during recessions (e.g. Perez-Quiros and Timmermann (2000)) implies that GVD increases when discount rates are high and should therefore predict high aggregate stock market returns during such times. Third, as Bernanke, Gertler, and Gilchrist (1996) and Kashyap, Lamont, and Stein (1994) emphasize, the theory implies that the real effects of financial constraints are more pronounced during recessions. As such, GVD's forecasting ability should be stronger during economic downturns when credit constraints bind. Fourth, the financial accelerator hypothesis also implies that macroeconomic shocks are magnified by financing constraints. Consequently, GVD should forecast aggregate investment even after controlling for current market risk premium.[3] Lastly, the models in Bernanke and Gertler (1989) and Kiyotaki and Moore (1997) predict that firms with relatively low collateral will be most impacted by an economic shock. Hence, small firm investments and returns should be more sensitive to changes in GVD.

By and large, our results support the financial accelerator theory. In fact, the forecasting ability of GVD is quite strong and GVD performs remarkably well as a predictor of aggregate market returns and investment growth, both in absolute terms, as well as relative to traditionally used forecasting variables.[4] To the best of our knowledge, GVD is the only forecasting variable that

[2] We find that GVD rises during recessions and has a rank correlation of -24% with contemporaneous GDP growth. GVD also has local maxima during periods of financial market stress.

[3] This implication highlights the difference between the financial accelerator hypothesis and the Q-theory of investments, which implies that aggregate investments decrease with market risk premium. Hence according to the Q-theory of investment GVD could forecast aggregate investment because it is related to market risk premium.

[4] The variables we consider are: default spread, term spread, dividend-price ratio, net payout, smoothed price-

forecasts aggregate market returns and investment growth both in-sample and out-of-sample. In-sample, GVD significantly predicts quarterly non-overlapping market returns ($R^2 = 3.3\%$) and quarterly aggregate investment growth ($R^2 = 6.3\%$). Out-of-sample, GVD significantly predicts quarterly non-overlapping market returns ($R^2 = 6.4\%$) and quarterly aggregate investment growth ($R^2 = 5.6\%$). In out-of-sample tests with quarterly forecasting horizon, none of the benchmark variables have positive R^2s in predicting market returns and only the default spread significantly predicts aggregate investment growth.

Interestingly, GVD's forecasting ability arises from the combination of its components. As discussed above, prior research suggests that economic downturns result in changes in both components; we find, however, that although each component by itself is a significant predictor of market returns and real economic activity, the predictive ability is much greater when the two are combined. Furthermore, using both components to forecast market returns and aggregate investment growth not only improves overall predictive ability, but also increases the significance of each component. This improvement occurs because both components have coefficients of similar magnitudes in the predicting regressions and have low–in fact negative–correlations with each other. As such, combining the components results in a predictor with a larger signal to noise ratio.[5]

In addition to finding that GVD forecasts aggregate market returns and investment growth, we also find evidence consistent with all other three forecasting implications that we test. In particular, GVD's coefficient in forecasting market returns when GDP growth is below its median is five times as large than when GDP growth is above its median.[6] We also find that increases in GVD forecasts declines in real private fixed-investment growth even after controlling for current market risk premium. Finally, in regressions predicting the returns or the investment growth of the Fama-French ten size sorted portfolios using GVD, we find that GVD coefficients increase as we move from large to small stocks. Overall, our results are consistent with the literature that argues

to-earnings ratio, book-to-market ratio of the Dow Jones Industrial Average index, consumption-wealth ratio, investment-to-capital ratio, and changes in the average market illiquidity.

[5] This perhaps explains why prior research on SMB has not uncovered its ability to predict market returns, even though there is a great deal of literature that suggests it should be correlated with discount-rate variation (e.g. Perez-Quiros and Timmermann (2000) and Fama and French (1996))

[6] These results are also consistent with Henkel, Martin, and Nardari (2011), who find that the forecasting ability of common-market return predictors is higher during recessions.

that financial markets–in particular, access to external finance–have real effects.

GVD's forecasting ability is robust to the standard critiques in the market-predictability literature. To finalize our analysis, we examine GVD's ability to forecast market returns in greater detail, since prior research documents several potential statistical pitfalls in predicting market returns. For instance, Ang and Bekaert (2007) show that the evidence of predictability depends crucially on the choice of standard errors in overlapping forecasting regressions, while Ferson, Sarkissian, and Simin (2003) show that more highly-persistent variables are more likely to be found significant in the data mining for predictor variables.[7]

Our main contribution is to the empirical literature that examines the financial accelerator theory. Bernanke, Gertler, and Gilchrist (1996) point out that because of the challenges commonly encountered in establishing causal relationships, empirical research examines the financial accelerator theory through its cross-sectional implications. For instance Hubbard, Kashyap, and Whited (1995) and Whited (1992) test this theory by estimating the Euler equation from a formal model of investment and find that explicitly including financing constraints greatly improves the fit of the model. Even though the findings in these cross-sectional tests overall support the financial accelerator hypothesis, the key forecasting implications of the financing accelerator theory have not yet been established. In fact, the most studied measure of changes in the relative valuation of small versus large companies, SMB, does not significantly predict market returns by itself, suggesting that the financial accelerator does not exist. We reconcile this forecasting result with the cross-sectional results by showing that once we control for GVD_{NEW} in predicting market returns, the coefficient on GVD_{OLD} (the component of GVD strongly related to SMB) becomes significant.

Naturally, the interpretation of our results as tests of Bernanke and Gertler (1989) theory relies on the working hypothesis that firm size is a proxy for access to external finance. However, there

[7]In particular, we focus on predicting quarterly non-overlapping returns to avoid biases in standard errors of overlapping returns (Ang and Bekaert (2007)). We show that GVD is less likely to be data-mined, since it is less persistent than standard predictors (Ferson, Sarkissian, and Simin (2003)); that GVD's predictive ability is robust to the Stambaugh (1999) bias, excluding influential periods such as the oil shocks and the internet period, and alternative start dates for the out-of-sample evaluation period (Hansen and Timmermann (2012)). GVD's predictive ability is unlikely to arise due to lead-lag relations between small and large firm returns since GVD also predicts market returns after skipping a quarter between computing GVD and measuring market returns. Similarly, GVD's predictive ability is unlikely to arise from persistence in market returns, since GVD continues to predict market returns after controlling for lagged market returns.

is debate in the literature with respect to how well firm size proxies capital market access, because firm size is also related to many other variables such as stock liquidity and foreign exposure. It could be, for instance, that macroeconomic shocks have a disproportionate effect on aspects of the business of small firms that are not related to financing constraints, and that small firms respond by decreasing investment and financing. If this were the case, our results would not be due to a financing accelerator mechanism. Perhaps because of this, some papers use other proxies of access to external finance to test the theory's implications on the cross-section of expected returns. Lamont, Polk, and Saa-Requejo (2001) use an index based on Kaplan and Zingales (1997) (KZ index) and conclude that there is no evidence of a financial constraints factor, on the other hand, Whited and Wu (2006) use an index of access to external finance via an estimation of an investment Euler equation (WU index) and find that there is some evidence that financial constraints are a priced risk factor. In a recent study, Hadlock and Pierce (2010) examine a series of proxies for capital market access including the KZ and the WU indexes. They find that firm size is a particularly useful predictor of financial constraints, while the KZ index does not seem to reflect financial constraints well. Our use of firm size as a proxy of access to external finance is therefore consistent with Hadlock and Pierce (2010) results. Moreover, to eliminate the possibility that our results are due to aspects of the small firms' business that are unrelated to financing constraints, we show that our results hold even if we use the ability of firms to access public credit market rather than firm size to define GVD.

Our paper is also related to research that examines market return predictability and especially to recent research that responds to the Goyal and Welch (2008) critique. In an influential paper, Goyal and Welch (2008) find that the predictive ability of traditional forecasting variables has greatly diminished after the oil shocks of the 1970s and, as a result, none of these variables predict market returns out-of-sample. GVD's forecasting ability actually improves in the post oil-shock sample thereby addressing the Goyal and Welch (2008) critique. Also, our results complement those in Campbell and Thompson (2008), Rapach, Strauss, and Zhou (2010), van Binsebergen and Koijen (2010), Ferreira and Santa-Clara (2011), and Kelly and Pruitt (2012), all of whom develop alternate estimation techniques for expected returns that succeed in predicting market returns out-of-sample. The out-of-sample predictability for market returns that we document is comparable to that in these papers.[8] Relative to these papers, our contribution is to develop a new economically-motivated variable that also predicts macroeconomic variables.

The remainder of the paper proceeds as follows: Section 1 defines GVD. Section 2 describes the data used throughout the paper along with general summary statistics. Section 3 tests first two of the forecasting implications of the financial accelerator theory by providing an overview of GVD's ability to forecast aggregate market returns and aggregate investment growth. Section 4 tests whether GVD's forecasting ability is stronger during contractions and whether GVD's ability to forecast investment growth is robust to controlling to current market risk premium. Section 5 shows that small stocks are more sensitive to changes in GVD. Section 6 discusses the robustness of our results. Section 7 concludes.

1 GVD (Goliath versus David)

We define GVD as:

$$GVD^m_{t,\Delta t} = \ln(\frac{P_{m,t}}{P_{M,t}}) - \ln(\frac{P_{m,t-\Delta t}}{P_{M,t-\Delta t}}) \tag{1}$$

where $P_{m,t}$ is the sum of the market capitalization at time t of the m firms with the largest market capitalization at time $t-\Delta t$, $P_{m,t-\Delta t}$ is the sum of the market capitalization at time $t-\Delta t$ of the m firms with the largest market capitalization at time $t-\Delta t$, $P_{M,t}$ is the sum of the market capitalization of all firms in the market at time t, and $P_{M,t-\Delta t}$ is the sum of the market capitalization of all firms in the market at time $t-\Delta t$. That is, $GVD^m_{t,\Delta t}$ is the change in the log of the weight of the m largest firms at time $t-\Delta t$ in the market portfolio.

Note that GVD is not just the difference between the return of the portfolio of the m largest firms and the market portfolio. In fact, we show in the appendix that:

$$GVD^m_{t,\Delta t} = (ExR^m_{t,\Delta t} - ExR^M_{t,\Delta t}) + (G^m_{t,\Delta t} - G^M_{t,\Delta t}) \tag{2}$$

[8] For example, Kelly and Pruitt (2012) report that their three-pass regression filter beats other estimators with an out-of-sample R^2 of between 0.44% and 0.76% for monthly returns (Table 1 of their paper). For exactly the same evaluation period (1980-2009), GVD's out-of-sample R^2 is 0.99%.

where $ExR^m_{t,\Delta t}$ is the ex-dividend return (return related to price appreciation only) between t and $t-\Delta t$ of the portfolio of the m largest stocks at time $t-\Delta t$, and $G^m_{t,\Delta t}$ is the rate of growth of this portfolio due to new stock issuances. Similarly, $ExR^M_{t,\Delta t}$ and $G^M_{t,\Delta t}$ are the ex-dividend return and the growth rate of the market portfolio. The exact expressions for the rate of growth and ex-dividend return are in the Appendix. We refer to $(ExR^m_{t,\Delta t} - ExR^M_{t,\Delta t})$ and to $(G^m_{t,\Delta t} - G^M_{t,\Delta t})$ as the returns component (GVD_{OLD}) and the capital-raising component (GVD_{NEW}) of GVD respectively.

2 Data and summary statistics

In this section, we describe in detail how we construct GVD (Section 2.1), the variables we use to benchmark GVD's forecasting performance (Section 2.2), the variables we forecast using GVD (Section 2.3), and GVD's countercyclical behavior (Section 2.4).

2.1 Computing GVD

Our implementation of $GVD^m_{t,\Delta t}$ sets the period Δt equal to one year. A shorter period for Δt may introduce noise to GVD unrelated to business cycle information, while a longer period may eliminate variation related to business cycles. We calculate $GVD^m_{t,1}$ at the end of every quarter using data from the Center for Research in Security Prices (CRSP). We only use ordinary shares (CRSP codes 10 and 11) and returns from 1926:4 to 2011:4 to build our measure.

Any choice of m is inevitably arbitrary because the theory does not provide guidelines about which firms are much less vulnerable to constraints. We therefore examine the robustness of our results to different choices of m. To guide our choices, we plot the number of firms in the database in Figure 1. As this figure shows we have about 500 firms in the beginning of the sample in 1925. Our first choice of m is therefore 250. This choice implicitly assumes that the top 50^{th} percentile of the firms in market capitalization in 1925 are less constrained than the bottom 50^{th}. Naturally, the number of companies in the U.S. stock market has grown over time and is larger than 500 in the later part of the sample. The top 250 companies in the later part of the sample nonetheless still have much better access to financing than the rest of the listed firms. $GVD^{250}_{t,\Delta t}$ consequently captures the differential evaluation of constrained and less constrained companies over the entire sample. $GVD^{250}_{t,\Delta t}$ is computed from 1926:4.[9]

Our second choice of m is based on the Fama and French (1993) definition of the SMB factor. Fama and French (1993) use the median market capitalization of NYSE stocks to define SMB. We follow their criterion and define $GVD^{Median}_{t,\Delta t}$. That is, we set m equal to the number of firms that have market capitalization above the median NYSE listed stock at time $t-\Delta t$.[10] As $GVD^{250}_{t,\Delta t}$, $GVD^{Median}_{t,\Delta t}$ is computed from 1926:4.

Our third choice of m is based on a criteria used by Whited (1992) to proxy for companies with better access to external financing. Whited (1992) argues that firms with access to the public debt market are less financially constrained than are firms without access to this market. This motivates the use of the credit rating information as a proxy for financially constrained firms. We define $GVD^{Credit}_{t,\Delta t}$ as in Equation 1 where $P_{m,t}$ is the sum of the market capitalization at time t of the firms with a long-term credit rating at time $t-\Delta t$, and $P_{m,t-\Delta t}$ is the sum of the market capitalization at time $t-\Delta t$ of the firms with a long-term credit rating at time $t-\Delta t$. The credit rating information is the monthly Standard & Poor's (S&P) Long-Term Domestic Issuer Credit Rating from Compustat or RatingsXpress. The credit rating information is much sparse before 1964; we have credit information on fewer than 50 firms prior to this date. As a result, we start the computation of $GVD^{Credit}_{t,\Delta t}$ in 1964.

Each of the definitions of GVD has its own merits and limitations, however they are all consistent in the sense that they generate similar implications. $GVD^{250}_{t,\Delta t}$ is the simplest definition, however $GVD^{250}_{t,\Delta t}$ is perhaps the most ad hoc of the three. $GVD^{Median}_{t,\Delta t}$ is also ad hoc, but it is based on a criterion that has been extensively used in the literature. Arguably, $GVD^{Credit}_{t,\Delta t}$ is the measure that best matches the theory that we test, however, as we mentioned above, $GVD^{Credit}_{t,\Delta t}$ cannot be computed for the entire sample period because of data limitations. As we show below, all versions of GVD are highly correlated and they lead to similar results. Hence for brevity we focus our discussion on GVD^{250} and only discuss results for GVD^{Median} and GVD^{Credit} if they

[9] Our definition of size is based on CRSP permnos. Our results are robust to using permcos instead of permnos.

[10] Note that there is a slightly abuse of notation in this case because m is not constant through the entire sample. We use m instead of m_t for purposes of simplicity.

are different from GVD^{250}.

2.2 Benchmarks and Controls

We compare the forecasting performance of GVD with the performance of a series of predictors proposed in the literature. We focus our choice of benchmarks on predictors that are commonly used and on those that perform well in-sample according to Goyal and Welch (2008). The sources for each of these predictor variables are described in Table 1. We use three broad sets of predictors: interest rate variables, valuation ratios, and macroeconomic variables.

- Interest-rate variables: These are the default spread (DS) and the term spread (TS). DS is the difference between BAA and AAA bond yields, and TS is the difference in the yield of the 10-year Treasury note and the 3-month bill. Although Goyal and Welch (2008) find no evidence that these variables forecast aggregate stock returns even in-sample, we include them because they are commonly used in the literature (e.g. Fama and French (1989)) and may predict the other independent variables that we consider.

- Valuation ratios: The valuation ratios we use are the dividend-price ratio (DP) examined in Fama and French (1988), Campbell and Shiller (1988a) and in many other papers, the cyclically-adjusted price-earnings ratio (CAPE) from Campbell and Shiller (1988b), the book-to-market ratio of the Dow Jones Industrial Average index (BM) from Pontiff and Schall (1998), and the net-payment yield of all stocks using the CRSP data (CRSPNPY) from Boudoukh, Michaely, Richardson, and Roberts (2007).

- Macroeconomic variables: The macroeconomic variables we use are the consumption-wealth ratio (CAY) from Lettau and Lydvigson (2001), and the investment-to-capital ratio (IK) from Cochrane (1991). Since Goyal and Welch (2008) find that these variables predict stock returns in-sample, we include all of them as benchmarks for evaluating GVD's forecasting power.

- Liquidity variable: The liquidity variable we use is the quarterly change in the average of the Amihud (2002) across all the stocks in the sample. We include Amihud illiquidity measure to our set of benchmarks because Bouwman, Sojli, and Tham (2012) and Naes, Skjeltorp, and Odegaard (2011) show that Amihud illiquidity measure have some ability to forecast bond returns and investment growth.

In addition to these benchmark variables, some of our analyses also controls for:

- Real GDP Growth ($GDPG$): $GDPG$ is the change in logs of the quarterly real seasonally-adjusted GDP series from FRED, the online database of the St. Louis Federal Reserve.
- Merger activity: We collect all merger announcements from SDC database to create a variable that measures M&A activity. This variables is called $HIGHMERGE$ and it has value equal to one when the growth in the number of mergers announced in the last twelve months is above the median growth of announced mergers and has value zero otherwise.

2.3 Dependent variables

We forecast several variables using GVD in this paper. These include the equity risk premium and real private fixed investment growth, returns on the ten size sorted Fama-French portfolios and investment growth of firms with different sizes. All returns are arithmetic.

- The market risk premium ($MKTRF$): $MKTRF$ is the return of the value-weighted CRSP index over the risk-free rate. We primarily focus on forecasting quarterly non-overlapping market excess returns, where returns are measured in excess of the three-month risk-free rate from the CRSP risk-free rate file. For monthly excess returns, we use returns in excess of the monthly risk-free rate and for annual excess returns we compound the three-month risk-free rate to the annual frequency.
- Real Private Fixed Investment Growth ($PFIG$): Similarly, PFIG is the change in logs of quarterly real (quantity series) seasonally-adjusted private non-residential fixed investment from the Bureau of Economic Analysis.
- Returns on ten Fama-French size sorted portfolios: These returns are from Wharton Research

Data Services (WRDS). These are arithmetic quarterly returns in excess of the 3 month risk-free rate for the ten size sorted portfolios.

- Investment growth on ten size sorted portfolios: We first sum the annual capital expenditure for all firms with December fiscal year end in each size portfolio for each year. The investment growth is the change in this aggregate annual capital expenditure for each size sorted portfolio. As in the Fama-French portfolios, we use NYSE size breakpoints.

2.4 Summary Statistics

Table 1, Panel A displays summary statistics for each of the predictor variables used in this paper. The mean of $GVD_{t,1}^{250}$ is -2.4%. The negative sign of this mean is consistent with the increase in the importance of smaller firms in the stock market during our sample period. Note that since we measure GVD as a difference, we are robust to non-stationarity issues related to the increase in the share of small firms in the sample over time. The autocorrelation of $GVD_{t,1}^{250}$ when sampled at the quarterly frequency is 0.702, and 0.116 when sampled annually. In addition, Dickey-Fuller tests reject the unit-root null at the usual significance levels. These autocorrelations are smaller than the autocorrelation of the benchmark predictors in Panel A. At the quarterly frequency, autocorrelations of all benchmark variables are above 0.9, while at the annual frequency, autocorrelations are above 0.7. This is important, because prior research finds that the high persistence of predictor variables used in forecasting aggregate market returns can create statistical problems (e.g. Stambaugh (1999) and Ferson, Sarkissian, and Simin (2003)). Given GVD's relatively low persistence, we do not expect that the issues described in Stambaugh (1999) and Ferson, Sarkissian, and Simin (2003) are as serious for GVD as they are for some commonly used forecasting variables such as dividend-yield. This conjecture is confirmed in Section 6.1. The low persistence of GVD is also consistent with recent evidence in Kelly and Pruitt (2012) who find that their predictor is less persistent than are traditional variables. Also note that the summary statistics of $GVD_{t,1}^{Median}$ and of $GVD_{t,1}^{Credit}$ are similar to those of $GVD_{t,1}^{250}$.

Panel B of Table 1 displays the correlations between $GVD_{t,1}^{250}$, $GVD_{t,1}^{Credit}$, $GVD_{t,1}^{Median}$, GVD_{OLD}^{250},

GVD^{250}_{NEW}, annual returns on SMB, and the set of benchmark variables.[11] This panel reveals that the correlation between the three GVD measures is high, for instance the correlation between $GVD^{Median}_{t,1}$ and $GVD^{250}_{t,1}$ is about 0.8. The correlation between $GVD^{250}_{t,1}$ and SMB is -0.41. This relatively high correlation is not surprising because of the conceptual connection between the returns component of GVD and the size factor (see Equation 2). This high correlation arises from the return differential component of GVD, GVD_{OLD}. GVD^{250}_{OLD} has a correlation of -0.79 with SMB, while the capital raising component, GVD^{250}_{NEW}, has a correlation with SMB of the opposite sign of 0.39. We show in Section 3.3 that both components are important in forecasting market returns as well as macroeconomic indicators and that each component by itself is a much weaker predictor of these variables than is GVD. Also note that GVD^{250}_{NEW} and $CRSPNPY$ are related but distinct. The difference between the two is that $CRSPNPY$ is the net-payment yield of all stocks, while GVD^{250}_{NEW} is the difference in net equity issuance between the 250 largest firms and the market. Covas and Den Haan (2011) show that the latter difference is important for the cyclical properties of these variables. They find that aggregate issuances for the largest firms are slightly countercyclical, while small firm issuances are procyclical, with the degree of cyclicality increasing as size decreases. They also report that issuances by the largest 1% of firms are so large that they have a significant impact on the aggregate market issuances. Therefore even though equity issuances are procyclical for an overwhelming majority of firms, they are not procyclical in aggregate. We see that the correlation between GVD^{250}_{NEW} and $CRSPNPY$ is 0.34. Relative to other correlations, it is by no means extraordinary; for example, $CRSPNPY$ has higher absolute correlations with the investment-to-capital ratio IK.

Figure 2 plots the quarterly time series of $GVD^{250}_{t,1}$ from 1926:4 to 2011:4 along with NBER recessions. This plot clearly shows that $GVD^{250}_{t,1}$ rises during recessions and falls during expansions; that is, the weight of large firms in the stock market portfolio increases in recessions and decreases in expansions. The rank correlation of GVD with quarterly GDP growth is -24%. This suggests that in terms of valuations, giant "Goliaths" handle recessions better than small "Davids," but that "Davids" outperform "Goliaths" during expansions.

[11] For purposes of brevity, we do not report the results with GVD^{Credit}_{OLD}, GVD^{Credit}_{NEW}, GVD^{Median}_{OLD}, GVD^{Median}_{NEW}.

The figure also includes text-boxes that correspond to local maxima or minima of GVD that are not in recessions. The text-boxes contain the date of the maxima or minima and proximate events that had an impact on financial markets. Note that the event may be spread over several months or occur in a single month proximate to the local maxima or minima. Working chronologically backwards, the first text-box corresponds to the peak in GVD in April 2003. The United States invaded Iraq on March 19, 2003. The next text-box corresponds to a peak in September 1998. LTCM collapsed in September 1998, and was rescued in a bailout by a group of financial institutions under the supervision of the Federal Reserve on September 23, 1998. The next peak is in April 1997. In February 1997, the first of many Thai property developers announced a default on a dollar denominated loan, leading to speculative attacks on the Thai baht, and an eventual lifting of its peg to the US dollar in July 1997. These events culminated in the "Asian crisis" that impacted several Asian economies including Indonesia, Malaysia, Singapore and South Korea. The next box corresponds to a peak in May 1995; GVD rises from a trough of -9.6% in September 1993 to 0% in January 1994, remaining at that level until its peak of 0.2% in May 1995. This period corresponds to the "peso crisis" in Mexico. Mexico was forced to allow the peso to float against the US dollar on December 20, 1994, resulting in a severe devaluation of the peso and a rise in interest rates on Mexican debt over the next few months. Other notable peaks occur in September 1992 (corresponding to "Black Wednesday" when the United Kingdom withdrew from the Exchange Rate Mechanism (ERM) due to speculative attacks on the pound), "Black Monday" in October 1987, and August 1939 (on the eve of World War II – Germany invaded Poland on September 1, 1939).

Caballero and Krishnamurthy (2008) present a model in which there is greater "Knightian" uncertainty in periods of market stress, such as the collapse LTCM and the stock market crash in October 1987, resulting in a flight to quality. As described above, GVD has local maxima during such periods of stock market stress. This suggests that financial market variables such as GVD may be better at reflecting discount rate variation than are purely macroeconomic variables, not only because they are available in real-time, but also because they respond to periods of great uncertainty, where adverse outcomes *may not be eventually realized.*

Figure 2 also reveals two outliers in $GVD_{t,1}^{250}$ in 1963 and 1972. These outliers are related to the creation of the NASDAQ and the AMEX stock exchanges. (Also see the jumps in Figure 1 in these years.) These events lead to a drop in GVD as the addition of data from these new exchanges to the CRSP database increases the total market capitalization of the market. Rather than making ad-hoc adjustments to GVD to reflect these events, we leave the GVD series unchanged and show in Section 6.1 that GVD's forecasting performance is robust to excluding these events.

3 GVD's forecasting ability

In this section we document GVD's forecasting ability and benchmark it to that of traditional predictive variables used by prior research. We first examine the ability of GVD and our benchmark variables to forecast stock market excess returns and private fixed investment growth. Section 3.1 performs an in-sample analysis, while Section 3.2 performs an out-of-sample analysis. These sections examine univariate forecasting regressions with no controls and allows us to compare the forecasting ability of GVD with that of the benchmark variables. Section 3.3 analyzes which component of GVD drives its forecasting ability.

3.1 In-sample forecasting

We run the following forecasting regression:

$$f_{t+\Delta t} = \alpha + \beta \times Predictor_t + \varepsilon_{t+\Delta t} \tag{3}$$

where $f_{t+\Delta t}$ is one of the following: the excess return of the value-weighted market portfolio from $CRSP$ or investment growth. All predictor variables are known prior to the start of month t. The predictor variables are described in Panel A of Table 1.

We run the regression above for quarterly ($\Delta t = 3$ months) and annual ($\Delta t = 12$ months) forecasting periods. We forecast at the quarterly horizon to follow Rapach, Strauss, and Zhou (2010) in estimating this regression with non-overlapping returns. This is important because Ang and Bekaert (2007) show that the evidence of predictability with overlapping dependent variables depends crucially on the choice of standard errors in forecasting regressions. (We use Newey-West standard errors with 3 lags for our non-overlapping quarterly regressions.) We therefore estimate the forecasting regression at the quarterly non-overlapping frequency, as they is the cleanest setup in terms of statistical tests. We also forecast at the annual forecasting horizon because although longer horizon regressions do not help in establishing predictability statistical significance, they help in understanding the economic significance of predictability (see Cochrane (2001)). We use Newey-West standard errors with 6 lags for our annual forecasting regression with quarterly overlapping. We perform robustness tests such as alternative specifications for standard errors in Section 6.1 .

Table 2 shows the results of the regression above. Overall, GVD is the only variable that significantly forecasts both aggregate market returns and Real Private Fixed Investment Growth at the quarterly horizon at 5% significance. The next best predictor in terms of the number of series forecasted is the CAPE, which predicts market returns and investment growth at 10%. GVD also forecasts both aggregate market returns and investment growth at the annual forecasting frequency. The only predictors that forecast both dependent variables at the annual frequency are the investment-to-capital ratio (IK) and the term spread (TS).

The results in Panel A of this table indicate that GVD^{250} is a significant predictor of market excess returns at the quarterly non-overlapping frequency, with an R^2 of 3.3%. Campbell and Thompson (2008) present a simple metric to gauge the economic significance of return predictability: the increase in expected returns of a mean-variance investor from observing the predictor variable. Using this metric, a quarterly R^2 of 3.3% results in an increase in expected returns of 2.8% per year for an investor with a risk aversion coefficient of 5.[12] The R^2s of GVD^{250}'s forecasting regressions for market returns are generally higher than those of regressions that use the benchmark variables. The only exception is BM from Pontiff and Schall (1998).[13]. This result is also consistent with the findings in Perez-Quiros and Timmermann (2000), which imply that GVD_{OLD} increases in economic downturns when discount rates are high and should therefore predict high aggregate

[12] Note that although investor utility increases, the increase is less than that implied by the increase in expected returns alone, since there is also an increase in volatility due to greater investment in the risky asset.

[13] The results in this panel for the benchmark variables are, in general, consistent with those in Goyal and Welch (2008), except for the results related to CAY, where our R^2s are lower. However, we find similar results using CAY as those in Goyal and Welch (2008) if we use the same period as they do.

stock market returns in such times.

GVD^{250} predicts investment growth with R^2s of 6.9%. This result is consistent with the financial accelerator theory which predicts that investment will decline following an increase in credit constraints. The default spread (DS) and Amihud illiquidity (AMI) are the only benchmark variables that predict investment growth, with R^2s of 12.5% and 4.3% respectively. Our results regarding the Amihud illiquidity are consistent with those in Naes, Skjeltorp, and Odegaard (2011), while the results regarding the default spread are consistent with the financial accelerator hypothesis. It is also interesting to notice that GVD^{Credit} is a strong predictor of investment growth with a R^2s of 18.4%.

3.2 Out-of-sample forecasting

Goyal and Welch (2008) argue that it is important to examine whether models forecast out-of-sample for two reasons. First, out-of-sample regressions allow us to investigate whether forecasting relationships are stable over time, and second, they also help determine whether an investor could have used these relationships profitably in real-time. Table 3 reports results for out-of-sample predictions for aggregate market returns and investment growth using GVD and each of the benchmark variables in univariate predictions. These are based on expanding window estimations, with the evaluation period starting in 1975:1 and rolling forward quarterly for the two series. We do this analysis at the quarterly and yearly forecasting horizons. We choose 1975 as our initial start date so that we would have at least 20 years for the initial estimation of all predictive regressions, as well as to eliminate any effect that the 1973-1974 oil crisis might have had in the out-of-sample forecasting. We report the out-of-sample R^2 as constructed in Campbell and Thompson (2008). The out-of-sample R^2 for variable i in Table 3 is given by $OOS\ R_i^2 = 1 - \sum_{t=tOOS}^{T_i}(R_t - \widehat{R}_{i,t})^2 \ / \sum_{t=tOOS}^{T_i}(R_t - \overline{R}_t)^2$, where T_i is one quarter (year) after the end of the sample of predictor variable i for the quarterly (annual) forecasting horizon, $\widehat{R}_{i,t}$ is the forecasted market returns based on variable i, $\overline{R}_t$ is the mean of the equity premium from the beginning of the sample until $T_i - 1$, and $tOOS$ is 1975:1. Section 6.2 shows that the forecasting ability of GVD for the market is robust to alternate start dates. We follow Goyal and Welch (2008) in using the McCracken (2007) MSE-F to evaluate the statistical significance of out-of-sample predictive ability.

Table 3 shows that GVD is a far better out-of-sample predictor than any of the benchmarks. All GVD measures (GVD^{250}, GVD^{Credit} as well as GVD^{Median}) forecast the two series out-of-sample at the annual and quarterly forecasting horizon. The next best predictor is the default spread that predicts investment growth and stock returns at the annual forecasting horizon at ten percent statistical significance. However, the default spread does not predict market returns at the quarterly horizon. Specifically, GVD^{250}'s out-of-sample R^2 for market returns is 6.4% and none of the benchmarks have positive out-of-sample R^2 in predicting quarterly market returns. Of the benchmark variables. All versions of GVD successfully predict quarterly investment growth with OOS R^2 of 5.6% for GVD^{250}, 10.0% for GVD^{Median}, and 18.3% for GVD^{Credit}. In the set of benchmark predictors, only the default spread has positive OOS R^2 (14.1%). At the annual forecasting horizon, all the versions of GVD forecast both investment growth and aggregate market returns. GVD^{250}'s out-of-sample R^2 for market returns is 7.3% and for investment growth is 10.3%, both of which are statistically significant at 1% level. DS's out-of-sample R^2 for market returns is 2.0% and for investment growth is 2.7% and they are statistically significant at 10% level. The illiquidity measure (AMI) also forecasts investment growth at annual frequency with an out-of-sample R^2 equal to 2.4% significant at 1% level.

Overall, the results in this section are consistent with Perez-Quiros and Timmermann (2000) results, along with Bernanke and Gertler (1989) and Kiyotaki and Moore (1997) models. That is, the relative valuation of large companies with respect to the market portfolio (GVD) captures time-variation in business conditions and therefore predicts time-variation in discount rates and investment growth.

3.3 The source of GVD's strong forecasting ability

As described in Section 1, GVD can be written as the sum of two components. The first component, GVD_{OLD}, is the difference in returns (excluding dividends) of the largest firms and the entire market. The second component, GVD_{NEW}, is the difference between the growth in the capitalization of the largest firms due to new capital raised and the growth in the entire market capitalization due to capital raising. Net new capital is calculated implicitly. For example, net new capital for the largest firms is the aggregate market capitalization at time t of largest firms at the end of month $t-12$, minus the sum of the market capitalizations of these firms at the end of $t-12$ grown by their respective returns in the period excluding dividends.

In this section, we test to see whether GVD's forecasting ability arises solely from one of these components or whether both components are required. This question is important in understanding the mechanism underlying GVD's forecasting power, particularly in light of the fact that SMB does not forecast aggregate market returns. Moreover, if only one of the components is important, we can refine GVD to reflect only that component. Note that the financial accelerator hypothesis suggests that both components should predict future economic activity and market returns. Positive values for GVD_{OLD} mean that small firms have had lower returns than large firms, potentially indicating that the market expects access to external finance to be more difficult; similarly, high values for GVD_{NEW} imply that small firms have raised less net new capital as compared with large firms, consistent with external finance becoming more expensive for these firms.

The first panel of Table 4 shows that both components are important in predicting quarterly market returns. Each component is significant when both are used together to predict market returns. Also, imposing equal coefficients, as we implicitly do when using GVD, does not hurt predictive power. A formal test of the hypothesis that the coefficients of GVD^{250}_{OLD} and GVD^{250}_{NEW} are equal is not rejected (p-value 0.24). The R^2 is 3.3% with GVD and 3.5% when both components are used separately. The coefficient on each component in univariate forecasting regressions is not as large as when both components are used together. The coefficient on GVD^{250}_{NEW} rises from 0.67 to 0.92 when GVD^{250}_{OLD} is added. Similarly, the coefficient on GVD^{250}_{OLD} goes from 0.36 to 0.65 when GVD^{250}_{NEW} is added. Overall, these results indicate that the functional form of GVD is appropriate.

In the final specification, we find that the coefficient on SMB is insignificant when used to predict market returns by itself. Note that although SMB is correlated with GVD^{250}_{OLD}, GVD^{250}_{OLD} has significant forecasting ability by itself, whereas SMB does not. This suggests that focusing on the largest stocks like GVD^{250} does, helps in predicting market returns relative to SMB which is based on the median NYSE firm.[14] The final specification shows that SMB significantly predicts market returns when we also include the capital-raising component of GVD, GVD_{NEW}. This reinforces the importance of using both components in forecasting market returns. This result may explain why prior research on SMB has not uncovered its forecasting ability for market returns.

The second panel of Table 4 shows that both components are important in predicting quarterly investment growth. The forecasting results in Panel B of Table 4 are qualitatively similar to those in Panel A. The only clear difference is that GVD_{OLD} does not forecast investment growth by itself (t-statistic equal to -1.37). However, in the same way as in Panel A, GVD_{OLD} help the forecasting investment growth when it is combined with GVD_{NEW}

One intuitive explanation for these results is that both components of GVD capture different aspects of the same underlying phenomenon and therefore reinforce each other. When small firms have lower returns than large firms it possibly indicates that the market expects a period of economic stress, with costly external capital. When this is combined with lower net capital raised by small firms relative to large firms, this further confirms that capital is costly and that the low relative returns are not because of other reasons.

An interesting feature of GVD_{OLD} and GVD_{NEW} is their covariance structure. Panel C of Table 4 shows that the coefficient of GVD_{NEW} on a regression of GVD_{OLD} on GVD_{NEW} is negative and statistically significant (t-statistic equal to -5.52) indicating that the covariance between GVD_{OLD} and GVD_{NEW} is negative. This negative covariance is the econometric reason for the increase in coefficients going from univariate to bivariate prediction regressions. The fact that both components forecast market returns and investments in the same direction suggests that news about economic distress affects them in the same way. Therefore, the negative correlation must arise from effects that are not related to future aggregate economic activity but are perhaps related to firm or industry specific news. For example, larger firms may raise more capital for investments as a response to large positive returns of smaller companies. In this case, the covariance between GVD_{NEW} and GVD_{OLD} is negative because the difference in covariances,

[14] In untabled results, we find that GVD_{OLD}^{Median} and GVD_{OLD}^{Credit} do not predict market returns by itself either. The point estimate of GVD_{OLD}^{Median} coefficient predicting market returns by itself is 0.64 with a t-statistic of 1.4. The point estimate of GVD_{OLD}^{Credit} coefficient predicting market returns by itself is 0.22 with a t-statistic of 1.12 for a sample period starting in 1964.

$cov[ExR^m_{t,\Delta t}, GVD_{NEW}] - cov[ExR^M_{t,\Delta t}, GVD_{NEW}]$, is negative. Another related example is the one of a consolidation wave in an industry that may cause potential acquirers (large firms) to raise capital at same time that the returns of targets (small firms) are high. This would lead to a negative correlation between GVD_{NEW} and GVD_{OLD} even when both are positively correlated with future market returns.

A full exploration of the economic reasons behind the negative sign of the covariance between GVD_{NEW} and GVD_{OLD} is not the objective of this paper. We however offer some preliminary evidence that this negative covariance has an underlying economic rational. We do so, by examining whether the coefficient of GVD_{NEW} in the regression of GVD_{OLD} on GVD_{NEW} changes during periods of high M&A activity.[15] Specifically, we measure M&A activity with a dummy variable called $HIGHMERGE$ which has value equal to one when the growth in the number of mergers announced in the last twelve months is above the median growth of announced mergers. Then we regress GVD_{OLD} on GVD_{NEW} and $HIGHMERGE$ interacted with GVD_{NEW}. The third column of Panel C of Table 4 shows the results of this regression. These results indicate that in fact the negative coefficient of GVD_{NEW} is largely driven by periods in which $HIGHMERGE$ is one.

4 Is GVD's forecasting ability countercyclical?

We have shown in Section 3.1 that GVD significantly predicts investment growth in univariate forecasting regressions; in this section we examine whether GVD's forecasting ability survives additional controls. In particular, the Bernanke and Gertler (1989) model implies that an increase in GVD is correlated with greater difficulty in accessing external finance and should therefore predict lower aggregate investment even when we control for current economic conditions, including expected market returns. This implication highlights the difference between the financial accelerator hypothesis and the Q-Theory of investments. In fact, the Q-Theory of investments implies that higher expected returns should be associated with lower aggregate investment. Consequently, it is possible that GVD forecasts investment growth because it forecasts aggregate market returns. As a result it is interesting to analyze whether GVD ability to forecast investment growth is due to

[15] The sample period for this regression starts in 1985 because data on merge activity before this date is sparse.

its ability to forecast market returns. In addition, the Bernanke and Gertler (1989) model implies that the financing constraints bind in recessions. We therefore examine whether GVD's effect on market returns is asymmetric in recessions versus expansions.

Table 5, Panel A shows the regressions predicting investment growth and market returns using GVD. The Bernanke and Gertler (1989) model also implies that credit constraints bind during periods of low economic growth, which in turn implies that GVD's forecasting ability should be higher during such times. We test this hypothesis using a dummy variable, LowGDP. LowGDP is one if the prior quarter's (quarter t when predicting returns for quarter $t+1$) GDP growth is below its time-series median and zero otherwise. We include LowGDP, as well as an interaction of LowGDP with GVD as predictive variables to forecast the two dependent variables we consider in this paper. We find that the interaction is of the expected sign and is statistically significant for both investment growth and market returns. In particular, the coefficient for predicting market returns on GVD is 0.264 (t-value 1.26) and that on the interaction of GVD with LowGDP is 1.113 (t-value 2.99). That is in periods of low GDP growth, the impact of a change in GVD on future market returns is 1.377, which is more than five times the coefficient on GVD when GDP growth is above its median. Thus, expected market returns are only sensitive to changes in GVD in bad times. This asymmetry is predicted by the Bernanke and Gertler (1989) model, since financing constraints bind during downturns in the model. Similarly, the interaction term is significant in predicting investment growth. Overall, these results strongly support the hypothesis that GVD's forecasting ability is more pronounced in recessions than in expansions.

Table 5, Panel B examines whether GVD's ability to predict quarterly and annual investment growth is related to time-variation in risk premium. We use two methodologies to address this question. The first methodology is to decompose GVD into two components: $GVDP$ is the value of GVD predicted by future market return and $GVDR$ is the component of GVD orthogonal to $GVDP$. We then regress future investment growth on these two components. Specification 1 Table 5, Panel B shows the results of this regression done at both quarterly and annual forecasting horizon. The results indicate that $GVDR$ forecasts investment growth while $GVDP$ does not. The second methodology is to predict the market risk premium with the regression:

$$MKTRf_{t+1,t+\Delta t} = a + b \times CAY_t + c \times CAPE_t + d \times IK_t + \varepsilon_{t+\Delta t} \tag{4}$$

$MKTP$ is the predicted market risk premium and $MKTR$ is the residual. We then regress investment growth on $MKTP$, $MKTR$ and GVD. The results indicate that the predicted market risk risk premium does not forecast investment growth at quarterly frequency, it forecasts investment growth however at ten percent significance using annual forecasting frequency. The results also show that neither $MKTP$ nor $MKTR$ subsumes $GVD's$ ability to forecast market returns. Overall, the results of both methodologies indicate that $GVD's$ ability to forecast investment growth is not due to its ability to forecast market risk premium. This is interesting because an alternative to the financial accelerator hypothesis to explain the relation between financial market shocks and investment growth is the Q-Theory of investment. Specifically, the Q-Theory indicates that investment decreases when market risk premium increases, the financial accelerator hypothesis, on the other hand, implies that investment decreases because some firms are financially constrained during downturns. The results in Table 5, Panel B are consistent with the implications of the financial accelerator hypothesis but they are not consistent with the Q-Theory of investments.

5 Are small firms more sensitive to changes in GVD?

Both the Kiyotaki and Moore (1997), and Bernanke and Gertler (1989) models predict that small firms are likely to be more financially constrained than large firms. Credit constraints impact investment through the value of collateral in these models. As Bernanke and Gertler (1989) and Kiyotaki and Moore (1997) note, firms with a high fraction of assets that are difficult to collateralize will find it harder to access external capital during downturns. This suggests that small firms will be more sensitive to changes in GVD, as compared to large firms that have a greater fractions of assets in place.

Table 6, Panel A presents results of predicting quarterly excess returns for ten size sorted portfolios using GVD. Portfolios are formed based on NYSE size breakpoints. The results indicate that the coefficients on GVD increase from large to small stocks portfolios. Note that since large stocks are less volatile than small stocks, the R^2 in regressions predicting returns of the largest stocks portfolio is amongst the highest of the ten size sorted portfolios at 3.2%. This indicates GVD's success in predicting value-weighted market returns stems from its ability to predict the largest stocks in the economy. A possible way to explain $GVD's$ ability to forecast the returns of size-sorted portfolios is that $GVD's$ forecasts market returns. To address if this is indeed the case, we forecast the returns of size-sorted portfolios with the component of GVD that is related to future market returns ($GVDP$) and with the component of GVD that is orthogonal to future market returns ($GVDR$). The results indicate that GVD forecasts the returns of size-sorted portfolios because it forecasts market returns.

Table 6, Panel B shows the results of forecasting investment growth for firms in each size decile. The results indicate that small firms investments are more sensitive to changes in GVD consistent with the hypothesis that firm size is related to access to external sources of finance. Interestingly, the results with respect to investment growth contrast with those related to returns because the component of GVD that forecasts investment growth is the one orthogonal to market risk premium ($GVDR$).

6 Robustness

In this section, we provide a detailed analysis of GVD's ability to predict market returns. There is a long literature that highlights statistical issues related to aggregate stock market return predictability. We examine whether GVD's ability to predict market returns is robust to these critiques, as well as other possible critiques specific to GVD. Section 6.1 examines in-sample prediction of market returns, while Section 6.2 examines out-of-sample prediction.

6.1 Predicting market returns in-sample

As another test of GVD's forecasting power, we analyze whether GVD merely summarizes the information that is already contained in predictor variables that are traditionally used in the literature. To do so, we run multivariate, in-sample, quarterly, non-overlapping regressions of aggregate stock market returns and investment growth on our set of benchmark predictors and GVD. The results of these regressions are in Table 7. We examine three groups of predictor variables: interest rates, valuation ratios, and macroeconomic variables. We also combine these predictors into two "Kitchen-sink" regressions. The first one contains all variables for which we have a long sample of data (1927:2 onwards) and the second contains all variables, thereby shortening its sample (1952:2 onwards). The hypothesis that the coefficient on GVD is equal to zero is rejected at the usual significance levels in all regressions in Table 7. The coefficient on GVD changes very little across specifications as well. These results confirm that GVD contains information relevant for forecasting aggregate returns and investment growth that is not in the usual predictors in the literature.[16]

Table 8 reports results of regressions predicting market excess returns with GVD. Panel A shows that GVD's statistical significance in forecasting quarterly market returns is robust to alternative specifications of standard errors. We report Ordinary Least Squares (OLS), Stambaugh bias-corrected (coefficients and standard errors) as well as Newey-West standard errors. We use the Amihud and Hurvich (2004) method to correct for the Stambaugh bias. The results in this panel reveal that there is only a small difference between the point estimates and the standard errors obtained with OLS compared to those obtained with the Stambaugh correction. This contrasts strongly with the results in Stambaugh (1999) using dividend-yield as the equity premium predictor. To understand the difference, note that this bias is due to the fact that $E[\varepsilon_{t+\Delta t}|y_{t+\Delta t},\, y_t] \neq 0$ in the regressions $R_{t+\Delta t} = \alpha + \beta \times y_t + \varepsilon_{t+\Delta t}$ and $y_{t+\Delta t} = \gamma + \rho \times y_t + v_{t+\Delta t}$, where y_t is either the dividend-yield or $GVD^{250}_{t,1}$. The relatively large bias in the forecasting regression when dividend-yield is the predictor is because ρ is relatively large and variations in the dividend-yield are mostly due to variations in prices rather than in dividends, hence $E[\varepsilon_{t+\Delta t}|y_{t+\Delta t},\, y_t]$ is further away from zero. On the other hand, GVD is not as persistent as aggregate dividend-yield, and variations in GVD are due to variations in both the market-price level and the valuations of large firms, thereby reducing the bias considerably.

Panel B of Table 8 shows the results of the forecasting regression above for different sample periods. Goyal and Welch (2008) note that many of the equity premium forecasting regressions

[16] In unreported results we find the GVD's forecasting performance is unaffected by controlling for two other variables evaluated by Goyal and Welch (2008), net equity expansion ($ntis$) and the cross-sectional premium (csp) from Polk, Thompson, and Vuolteenaho (2006).

commonly described in the literature are not robust to different sample periods. We therefore look to see if this is the case with GVD and find that GVD's forecasting power for the early sample period (1927:1 to 1955:2) is weaker than that for later periods. The coefficient on GVD in the early sample period is borderline insignificant with a t-statistic of 1.43 and a p-value of 15%, while the R^2 is 2.5% compared with 6.8% and 3.8% for the periods from 1955:3 to 1983:3 and 1983:4 to 2011:4, respectively. The improvement in the forecasting ability of GVD over time is perhaps related to the change in the sample composition of publicly listed firms documented by Fama and French (2004). Over the later part of the sample, smaller, less profitable firms have been able to list on public equity markets. The valuations of these firms are likely to be more sensitive to shocks to financial access, thereby improving the performance of GVD in capturing discount rate variation.

Panel C examines whether all three versions of GVD also forecast monthly market returns. We find that all three versions are significant, with slightly higher $R^{2\prime}$s for GVD^{250} and GVD^{Median} as compared to that of GVD^{credit}.

Panel D presents an analysis of the robustness of GVD's forecasting power. To do this, we estimate different variations of the regression forecasting quarterly market excess returns. The first two specifications explore robustness to the inclusion of data from new exchanges. In the first year of the NASDAQ and the AMEX, the denominator of GVD increases substantially, as the capitalization of the overall market increases with the inclusion of new firms; however, the numerator is unaffected, leading to drops in GVD. The first specification includes a dummy variable (NEWEX) that has a value of one in the years in which NASDAQ and AMEX stocks are included in the CRSP database. The next specification excludes the two years in which these exchanges are included in the CRSP universe. The coefficient on GVD is virtually unaffected across these specifications. Specification "Ex-1970s" excludes the 1970s to examine the importance of the oil shocks, and specification "Ex-Internet" ends the sample in 1997:1 to remove the influence of the Internet period. These specifications show that GVD's forecasting ability is not driven by these influential periods. Specification "FF" adds returns on the three Fama-French factors, the market, HML, and SMB over the prior year. The annual horizon is chosen to mimic the period used in computing GVD. We include the market to examine whether persistence in market returns (as in Connolly and Stivers (2003)) or lead-lag relations between small and large stocks (as in Lo and MacKinlay (1990)) drives our results. The coefficient on GVD is unaffected–and in fact increases slightly–in this specification and none of the annual returns on the Fama-French factors are significant. Finally, we skip a quarter between measuring GVD and forecasting returns: GVD is computed from month $t-12$ to $t-1$, and market returns are from $t+2$ to $t+5$, skipping a quarter. This provides another method of ruling out the hypothesis that lead-lag effects or other microstructure biases affect our results. The coefficient on GVD drops from 0.76 to 0.55, but retains its statistical and economic significance in this specification.[17]

Overall, these regressions show that the forecasting power of GVD is robust: GVD remains a significant predictor of market excess returns in all specifications. GVD's forecasting power is robust to alternate definitions for GVD, monthly and annual horizons, and is not due to the inclusion of new exchanges in the CRSP universe, the oil crisis, the internet period, or lead-lag relations between large and small stock returns.

6.2 Predicting market returns out-of-sample

To analyze GVD's out-of-sample forecasting power, we follow the Goyal and Welch (2008) methodology. Specifically, for each quarter (T), we calculate $\Delta SSE_T = \sum_{t=tOOS}^{T}(R_t - \overline{R}_t)^2 - \sum_{t=tOOS}^{T}(R_t - \widehat{R}_t)^2$ where $\overline{R}_t$ is the mean of the equity premium from the beginning of the sample (1927:1) until $T-1$, $\widehat{R}_t$ is the equity premium forecasted with an OLS regression of aggregate market returns on GVD, which is estimated with the sample from 1927:1 to $T-1$, and $tOOS$ is the beginning of the out-of-sample period.

Figure 3 plots ΔSSE_T as a function of time T, for quarterly predictions in Panel A, and annual predictions (with quarterly overlap) in Panel B. We set tOOS=1947:1, allowing for a 20-year initial training sample. Negative values of ΔSSE_T in this figure imply that GVD is worse than the running-mean equity premium in forecasting market excess returns out-of-sample. On the other hand, positive values of ΔSSE_T imply that GVD has a better forecasting performance than the running-mean equity premium. This figure shows that the out-of-sample forecasting performance

[17] In unreported tests, we find that GVD is significant in predicting quarterly market returns even after skipping up to three quarters, though the coefficients diminish in magnitude.

of GVD has been better than that of the running mean since the 1970s. Note that in 1962 the forecasting performance of GVD deteriorates substantially due to the inclusion of AMEX stocks in the CRSP universe. On the other hand, the 1973-1974 oil crisis along with the inclusion of NASDAQ stocks in 1972 improves GVD's forecasting performance. We therefore investigate the statistical significance and robustness of our out-of-sample results to different start dates for the evaluation period in Table 9.

Table 9 reports out-of-sample R^2s for evaluation periods beginning every decade from 1947:1 to 1987:1.[18] Although out-of-sample R^2s vary across periods, they are uniformly positive for, GVD^{250} and GVD^{Median} in quarterly predictions in Panel A and annual (with quarterly overlap) predictions in Panel B. In order to evaluate the statistical significance of these results, we report p-values for the MSE-F test of equal predictive ability in McCracken (2007). The null hypothesis in this test is that two nested models have equal predictive ability out-of-sample, and the one-sided alternative is that the more complex model has better predictive ability. We test whether $\overline{R}_t$ (the historical market mean) and $\widehat{R}_t$ (the prediction from GVD) have equal predictive ability for market excess returns. Both out-of-sample forecasts utilize expanding-window estimation periods. The p-values in Panel A are asymptotic values from McCracken (2007). P-values in Panel B are from a bootstrap procedure, similar to that in Goyal and Welch (2008), except that we use a block bootstrap to account for the quarterly overlap in annual market returns.[19] We can reject the hypothesis that GVD and the running-mean have equal predictive ability, in favor of GVD, for all specifications.

7 Conclusion

We show that the relative valuation of small and large firms is a real-time indicator of aggregate economic conditions. Large firms are able to withstand recessions better than small firms, and their valuations reduce by less during such times. This is consistent with the implications of financial accelerator hypothesis, which states that following adverse economic shocks, the decline in value of small firm balance-sheets makes it harder for small firms to access external finance leading to a

[18] Table 9 does not report out-of-sample R^2s using GVD^{Credit} because GVD^{Credit} time series is shorter.

[19] We use a block length of 4, which is of the order of magnitude of $n^{0.25}$ (see Hall, Horowitz, and Jing (1995)). We get similar results for block lengths between 1 and 8.

decrease in aggregate investment and an amplification of the original shock.

GVD's forecasting performance is impressive. We show that GVD predicts market returns and investment growth. We find that all the usual predictors of quarterly aggregate stock market returns have negative out-of-sample R^2s, while GVD is the only predictor that has a positive out-of-sample R^2. In fact, GVD's out-of-sample R^2 is not only positive but is also economically highly significant. Moreover, GVD is the only predictor that forecasts market returns and investment growth both in sample and out-of-sample at annual and quarterly forecasting horizon.

GVD has two components, one component is the difference in the returns of large firms and of the market, the other component is the difference in the growth of large firms and of the market due to capital raising. GVD strong forecasting ability stems from the combination of its components. Each of $GVD's$ components can be seen as a forecast of future economic activity plus some noise. The combination of both components in GVD has higher signal-to-noise ratio because the noise pieces in each of the $GVD's$ components are negatively correlated.

The results of our tests support the financial accelerator theory. We show that GVD predicts returns and investment growth of size sorted portfolios, and that GVD forecasting ability is countercyclical. Moreover, consistent with the financial accelerator hypothesis, $GVD's$ ability to forecast investment growth is robust to controlling for the predicted equity premium. This result highlights that GVD ability to forecasting investment growth is not explained by the Q-Theory of investment, which implies that investment growth decreases with market risk premium. We also show that GVD's ability to forecast market returns is robust to standard critiques in the predictability literature and is not due to information contained in traditional variables, such as SMB and net payout.

In conclusion, GVD's strong forecasting ability along with the extent to which our results are consistent with the financial accelerator hypothesis indicate that shocks to financial access and fluctuations in real economic activity are strongly tied.

Appendix A - Decomposing GVD

In this appendix we show that $GVD^m_{t,\Delta t}$ can be decomposed in two components. One component is the difference in ex-dividend returns of the portfolio with m stocks and of the market portfolio. The second component is the difference in capital raised by the m largest firms in $t-\Delta t$ and the capital raised by the rest of the market. To see this note that:

$$GVD^m_{t,\Delta t} = \ln(\frac{P_{m,t}}{P_{M,t}}) - \ln(\frac{P_{m,t-\Delta t}}{P_{M,t-\Delta t}}) \tag{5}$$

Where $P_{m,t}$ is equal to sum of the market capitalization at time t of the m largest firms in the market portfolio at time $t-\Delta t$ and $P_{M,t}$ is the sum of the market capitalization at time t of all the firms in the market portfolio. $GVD^m_{t,\Delta t}$ can be rewritten as:

$$GVD^m_{t,\Delta t} = \ln P_{m,t} - \ln P_{m,t-\Delta t} - (\ln P_{M,t} - \ln P_{M,t-\Delta t}) \tag{6}$$

Note that $P_{j,t} = \sum_{i=1}^{K_j}(N^i_{t-\Delta t}+\Delta N^i_t)p^i_t$, $j = m$ or M, where $N^i_{t-\Delta t}$ is the number of shares of the ith firm in the portfolio, ΔN^i_t is change in the number of shares between t and $t-\Delta t$, p^i_t is the price of the ith firm at time t, and K_j is the number of stocks in the portfolio. An algebraic manipulation of $P_{j,t}$ implies that $\ln(P_{j,t})$ is equal to $\ln(\sum_{i=1}^{K_j} N^i_{t-\Delta t}p^i_t)$ plus $\ln(\sum_{i=1}^{K_j}(N^i_{t-\Delta t}+\Delta N^i_t)p^i_t/\sum_{i=1}^{K_j} N^i_{t-\Delta t}p^i_t)$. Substituting this expression for $P_{j,t}$ in the equation above, we get:

$$\begin{aligned} GVD^m_{t,\Delta t} \;=\; & (\ln \frac{\sum_{i=1}^{m} N^i_{t-\Delta t}p^i_t}{\sum_{i=1}^{m} N^i_{t-\Delta t}p^i_{t-\Delta t}} - \ln \frac{\sum_{i=1}^{M} N^i_{t-\Delta t}p^i_t}{\sum_{i=1}^{M} N^i_{t-\Delta t}p^i_{t-\Delta t}}) + \\ & (\ln \frac{\sum_{i=1}^{m}(N^i_{t-\Delta t}+\Delta N^i_t)p^i_t}{\sum_{i=1}^{m} N^i_{t-\Delta t}p^i_t} - \ln \frac{\sum_{i=1}^{M}(N^i_{t-\Delta t}+\Delta N^i_t)p^i_t}{\sum_{i=1}^{M} N^i_{t-\Delta t}p^i_t}) \end{aligned} \tag{7}$$

The term within the first parentheses of the equation above is the difference between the ex-dividend return of the portfolio of large stocks and of the market portfolio. The term within the second parentheses is the difference between the growth due to share issuance of the portfolio of large stocks and of the market portfolio. Call $ExR^j_{t,\Delta t} = \ln \sum_{i=1}^{K_j} N^i_{t-\Delta t}p^i_t/\sum_{i=1}^{K_j} N^i_{t-\Delta t}p^i_{t-\Delta t}$ and

$G^j_{t,\Delta t} = \ln(\sum_{i=1}^{K_j}(N^i_{t-\Delta t} + \Delta N^i_t)p^i_t / \sum_{i=1}^{K_j} N^i_{t-\Delta t}p^i_t)$ to write:

$$\begin{aligned} GVD^m_{t,\Delta t} &= (ExR^m_{t,\Delta t} - ExR^M_{t,\Delta t}) + (G^m_{t,\Delta t} - G^M_{t,\Delta t}) && (8) \\ GVD^m_{t,\Delta t} &= GVD_{OLD} + GVD_{NEW} && (9) \end{aligned}$$

We implement this decomposition in the data using returns excluding dividends from CRSP, $r^x_{t-12,t}$. We first compute the value of capital at time t, that existed at time $t-12$, $P^{exist}_{j,t}$ as:

$$\begin{aligned} P^{EXIST}_{j,t} &= \sum_{i=1}^{j} P_{i,t-12}(1 + r^x_{i,t-12,t}) && (10) \\ ExR^j_{t,\Delta t} &= \ln(\frac{P^{EXIST}_{j,t}}{P_{j,t-12}}) && (11) \end{aligned}$$

where $j = m$ or M. We compute GVD_{OLD} from $ExR^m_{t,\Delta t}$ and $ExR^M_{t,\Delta t}$. We compute net new capital as:

$$P^{NEW}_{j,t} = P_{j,t} - P^{EXIST}_{j,t} \qquad (12)$$

where $j = m$ or M. We compute GVD_{NEW} from $P^{NEW}_{j,t}$ and $P_{j,t}$ as described above.

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Table 1: Summary statistics

This table presents statistics for GVD^{250}, GVD^{Median}, GVD^{Credit}, and our set of benchmark predictors for market excess returns. GVD is the change in the log weight of the least constrained firms in the aggregate market portfolio over the last 12 months. The least constrained firms are the largest 250 firms (GVD^{250}), firms larger than the NYSE median (GVD^{Median}), or firms that have a credit rating (GVD^{Credit}). The benchmark predictors include interest rate variables, DS and TS (default and term spreads); valuation ratios, DP, CAPE, BM, CRSPNPY (dividend to price, cyclically adjusted price to earnings, book-to-market of the DJIA, and log net payout of all CRSP stocks); macro variables, CAY and IK (consumption-wealth ratio, and investment-to-capital ratio); and AMI (quarterly changes in the average of the Amihud illiquidity measure across all stocks). Panel A presents summary statistics. These include mean, standard deviation, minimum and maximum. Panel A also presents autocorrelations at quarterly (overlapping for GVD) and annual (non-overlapping) horizons. Panel B presents correlations between GVD^{250}, GVD^{500}, GVD_{OLD}, GVD_{NEW}, annual returns on the Fama-French factors, MKTRF12, SMB12, HML12, and the benchmark predictors. GVD_{OLD} and GVD_{NEW} are the two components of GVD. GVD_{OLD} is the difference in returns on existing capital between the top 250 firms and market, and GVD_{NEW} is the difference in net equity issuance between the top 250 firms and the market. Web addresses for the sources of each of the benchmark predictors are:

FRED: http://research.stlouisfed.org/fred2/
Shiller: http://www.econ.yale.edu/~shiller/data.htm
Goyal: http://www.hec.unil.ch/agoyal/
Roberts: http://finance.wharton.upenn.edu/~mrrobert/

Panel A: Summary statistics

	Start	End	Source	Mean	Std	Min	Max	ρ1 Qtr	ρ1 Ann
GVD^{250}	1926:4	2011:4	This paper	-0.02	0.03	-0.12	0.07	0.70	0.11
GVD^{Median}	1926:4	2011:4	This paper	-0.02	0.02	-0.14	0.02	0.72	0.10
GVD^{Credit}	1926:4	2011:4	This paper	-0.02	0.04	-0.16	0.14	0.73	-0.05
DS	1926:3	2011:4	FRED	0.01	0.01	0.00	0.06	0.90	0.71
TS	1926:3	2011:4	Shiller	0.02	0.01	-0.04	0.05	0.85	0.60
DP	1926:3	2011:4	Shiller	-3.33	0.45	-4.50	-1.98	0.97	0.88
CAPE	1926:3	2011:4	Shiller	17.46	7.22	5.57	44.20	0.97	0.88
CAY	1952:1	2011:4	Lettau	0.00	0.02	-0.04	0.04	0.92	0.72
IK	1947:1	2011:4	Goyal	0.04	0.00	0.03	0.04	0.96	0.73
BM	1926:3	2011:4	Goyal	0.59	0.27	0.13	2.03	0.94	0.84
CRSPNPY	1927:1	2010:4	Roberts	-2.14	0.22	-3.14	-1.53	0.95	0.73
AMI	1926:4	2011:4	This paper	-0.01	0.44	-1.56	1.14	-0.11	-0.09

Table 1: Summary statistics (contd.)

Panel B: Correlations

	GVD^{250}	GVD^{Median}	GVD^{Credit}	GVD_{OLD}	GVD_{NEW}	MKTRF12	SMB12	HML12	DS	TS	DP	CAPE	CAY	IK	BM	NPY	AMI
GVD^{250}	1.00	0.89	0.62	0.61	0.38	-0.27	-0.51	-0.21	0.26	-0.09	0.18	-0.17	0.12	-0.05	0.14	0.26	0.10
GVD^{Median}	0.89	1.00	0.69	0.39	0.67	-0.26	-0.31	-0.15	0.19	0.01	0.21	-0.26	0.03	-0.20	0.24	0.32	0.10
GVD^{Credit}	0.62	0.69	1.00	0.37	0.39	-0.39	-0.42	0.34	0.19	0.06	0.18	-0.20	0.15	-0.11	0.10	0.23	0.13
GVD_{OLD}	0.61	0.39	0.37	1.00	-0.31	-0.33	-0.89	-0.21	0.34	-0.17	-0.09	0.11	0.21	0.11	-0.19	-0.10	0.29
GVD_{NEW}	0.38	0.67	0.39	-0.31	1.00	-0.07	0.30	0.07	-0.06	0.08	0.34	-0.39	-0.22	-0.26	0.45	0.42	-0.10
MKTRF12	-0.27	-0.26	-0.39	-0.33	-0.07	1.00	0.26	0.05	-0.46	-0.03	-0.17	0.18	-0.03	-0.19	-0.17	-0.08	-0.33
SMB12	-0.51	-0.31	-0.42	-0.89	0.30	0.26	1.00	0.03	-0.28	0.25	0.02	-0.10	-0.21	-0.03	0.15	0.08	-0.23
HML12	-0.21	-0.15	0.34	-0.21	0.07	0.05	0.03	1.00	-0.33	0.07	0.03	-0.08	0.05	0.06	0.11	0.10	-0.08
DS	0.26	0.19	0.19	0.34	-0.06	-0.46	-0.28	-0.33	1.00	-0.25	0.06	0.02	-0.03	0.18	-0.02	-0.13	0.22
TS	-0.09	0.01	0.06	-0.17	0.08	-0.03	0.25	0.07	-0.25	1.00	-0.07	-0.09	0.18	-0.45	-0.04	0.05	-0.08
DP	0.18	0.21	0.18	-0.09	0.34	-0.17	0.02	0.03	0.06	-0.07	1.00	-0.85	0.04	-0.17	0.84	0.80	0.12
CAPE	-0.17	-0.26	-0.20	0.11	-0.39	0.18	-0.10	-0.08	0.02	-0.09	-0.85	1.00	0.00	0.17	-0.91	-0.74	-0.09
CAY	0.12	0.03	0.15	0.21	-0.22	-0.03	-0.21	0.05	-0.03	0.18	0.04	0.00	1.00	-0.09	-0.16	0.04	0.06
IK	-0.05	-0.20	-0.11	0.11	-0.26	-0.19	-0.03	0.06	0.18	-0.45	-0.17	0.17	-0.09	1.00	-0.05	-0.25	0.17
BM	0.14	0.24	0.10	-0.19	0.45	-0.17	0.15	0.11	-0.02	-0.04	0.84	-0.91	-0.16	-0.05	1.00	0.73	0.07
CRSPNPY	0.26	0.32	0.23	-0.10	0.42	-0.08	0.08	0.10	-0.13	0.05	0.80	-0.74	0.04	-0.25	0.73	1.00	0.05
AMI	0.16	0.10	0.13	0.29	-0.10	-0.33	-0.23	-0.08	0.22	-0.08	0.12	-0.09	0.06	0.17	0.07	0.05	1.00

Table 2: Predicting stock market returns and investment growth in sample

This table presents results of regressions of the type:

$$Y_{t+\Delta t} = a + b\ \text{Predictor}_t + \varepsilon_{t+\Delta t}$$

The dependent variables are: (1) Quarterly arithmetic excess returns of the CRSP value-weighted index over the monthly risk-free rate, (2) Quarterly real Private Fixed Non-Residential Investment Growth (PFIG). All regressions have non-overlapping dependent variables. The predictor variables include interest rate variables, DS and TS (default and term spreads); valuation ratios, DP, CAPE, BM, CRSPNPY (dividend to price, cyclically adjusted price to earnings, book-to-market of the DJIA, and log net payout of all CRSP stocks); macro variables, CAY and IK (consumption-wealth ratio and investment-to-capital ratio); and AMI, (quarterly changes in the average of the Amihud illiquidity measure across all stocks) . These are described in greater detail in Table 1. All standard errors are Newey-West (with 3 lags for quarterly and 6 lags for annual regressions). The symbols ***, **, and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: Predicting market excess returns

	Quarterly (non-overlapping)				Annual (quarterly overlap)			
	a	b	R^2	N	a	b	R^2	N
GVD^{250}	0.038***	0.757***	3.3%	340	0.136***	2.283***	7.2%	337
GVD^{Median}	0.042***	1.021***	3.2%	340	0.156***	3.468***	9.2%	337
GVD^{Credit}	0.021**	0.376**	3.3%	191	0.081***	1.188**	7.6%	188
DS	-0.005	2.170	1.9%	340	0.016	5.733	3.2%	338
TS	0.010	0.594	0.5%	340	0.036	2.810**	2.6%	338
DP	0.133**	0.034*	1.8%	340	0.528***	0.134**	6.9%	338
CAPE	0.059***	-0.002**	2.1%	340	0.247***	-0.009***	8.8%	338
BM	-0.030	0.084**	4.0%	340	-0.087	0.286***	11.1%	338
NPY	0.188***	0.079**	2.4%	336	0.819***	0.345***	11.2%	336
CAY	0.017***	0.826***	2.7%	239	0.069***	3.190***	8.4%	236
IK	0.160***	-3.996***	3.0%	259	0.554***	-13.431**	7.1%	256
AMI	0.020***	0.007	0.1%	340	0.082***	0.013	0.1%	337

Table 2: Predicting stock market returns and investment growth in sample (contd.)

Panel B: Predicting investment

	Quarterly (non-overlapping)				Annual (quarterly overlap)			
	a	b	R^2	N	a	b	R^2	N
GVD^{250}	0.005*	-0.216***	6.3%	260	0.012	-1.033***	9.6%	256
GVD^{Median}	0.004	-0.331***	7.1%	260	0.010	-1.262**	7.0%	256
GVD^{Credit}	0.006**	-0.221***	18.4%	192	0.017	-0.777***	15.1%	191
DS	0.029***	-1.949***	12.5%	260	0.085***	-5.171**	5.9%	256
TS	0.010***	0.006	0.0%	260	0.012	1.473**	4.6%	256
DP	-0.014	-0.007	1.5%	260	-0.016	-0.015	0.5%	256
CAPE	0.001	0.000*	2.2%	260	0.018	0.001	0.6%	256
BM	0.016***	-0.010	1.0%	260	0.052*	-0.029	0.6%	256
NPY	-0.005	-0.007	0.4%	256	0.008	-0.012	0.1%	253
CAY	0.011***	-0.018	0.0%	239	0.036***	0.709	2.0%	239
IK	0.007	0.101	0.0%	260	0.211**	-4.934**	3.5%	256
AMI	0.010***	-0.014***	0.043	260	0.035***	-0.074***	8.5%	256

Table 3: Predicting stock returns and investment growth out-of-sample

This table presents results of out-of-sample predictions of a set of dependent variables using a set of predictor variables. The dependent variables include: (1) Quarterly arithmetic excess returns of the CRSP value-weighted index over the monthly risk-free rate, (2) Quarterly real Private Fixed Non-Residential Investment Growth (PFIG). The predictor variables include versions of GVD, GVD^{250}, GVDMedian, and GVDCredit, interest rate variables, DS and TS (default and term spreads); valuation ratios, DP, CAPE, BM, CRSPNPY (dividend to price, cyclically adjusted price to earnings, book-to-market of the DJIA, and log net payout of all CRSP stocks); macro variables, CAY and IK (consumption-wealth ratio and investment-to-capital ratio); and AMI (quarterly changes in the average Amihud liquidity measure across all stocks). These are described in greater detail in Table 1.We report out-of-sample R^2s from expanding window estimations, with the start date for the evaluation period beginning in 1975:1. Statistical significance is assessed based on MSE-F tests (McCracken (2007)) of equal predictive ability between using the historical mean market excess return and the predictor variable. The symbols ***, **, and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: Predicting market returns

	Quarterly		**Annual**	
Variable	OOS R^2	N	OOS R^2	N
GVD^{250}	6.4%***	148	7.3%***	145
GVD^{Median}	5.8%***	148	8.8%***	145
GVD^{Credit}	3.3%***	148	6.0%***	145
DS	-0.3%	148	2.0%*	145
TS	-2.3%	148	-5.1%	145
DP	-5.3%	148	-20.7%	145
CAPE	-8.8%	148	-47.1%	145
BM	-15.2%	148	-41.3%	145
CRSPNPY	-10.6%	145	-49.9%	145
CAY	-2.2%	148	-9.3%	145
IK	-1.4%	148	-3.8%	145
AMI	-0.6%	148	-0.1%	145

Table 3: Predicting stock returns and investment growth out-of-sample (contd.)

Panel B: Predicting investment growth

	Quarterly		**Annual**	
Variable	OOS R^2	N	OOS R^2	N
GVD^{250}	5.6%***	148	10.3%***	145
GVD^{Median}	10.0%***	148	10.4%***	145
GVD^{Credit}	18.3%***	148	9.1%***	145
DS	14.1%***	148	2.7%*	145
TS	-1.9%	148	-9.0%	145
DP	-6.2%	148	-6.6%	145
CAPE	-9.7%	148	-11.0%	145
BM	-13.6%	148	-14.4%	145
CRSPNPY	-5.3%	145	-9.4%	145
CAY	-2.1%	148	-3.1%	145
IK	-0.7%	148	-1.4%	145
AMI	-1.7%	148	2.4%***	145

Table 4: The components of GVD

This table presents results for regressions that predict: (1) Quarterly arithmetic excess returns of the CRSP value-weighted index over the monthly risk-free rate, (2) Quarterly real Private Non-Residential Fixed Investment Growth (PFIG). The predictor variables include GVD^{250} and its two components, GVD_{OLD} and GVD_{NEW}. GVD_{OLD} is the difference in returns (excluding dividends) between of the top 250 firms and the market over the last year, while GVD_{NEW} is the difference in net new equity capital issuance between the top 250 firms and the market over the past year. LNSMB12 is the log return on SMB over the past 12 months. All standard errors are Newey-West (with 3 lags). The symbols ***, **, and * represent statistical significance at the 1%, 5% and 10% levels, respectively. T-statistics are in parentheses.

Panel A: Predicting MKTRF

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Intercept	0.038***	0.042***	0.019***	0.036***	0.021***	0.044***
	(4.15)	(4.14)	(3.17)	(3.94)	(3.17)	(4.03)
GVD^{250}	0.757***					
	(3.74)					
GVD_{OLD}		0.645***	0.361*			
		(3.16)	(1.87)			
GVD_{NEW}		0.916***		0.666***		0.869***
		(3.47)		(2.86)		(3.25)
LNSMB12					-0.039	-0.101**
					(-0.83)	(-2.34)
R^2	3.3%	3.5%	0.6%	1.7%	0.2%	2.7%
N	340	340	340	340	340	340

Panel B: Predicting PFIG

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Intercept	0.005*	0.004	0.010***	0.005	0.010***	0.003
	(1.74)	(1.09)	(4.95)	(1.62)	(4.52)	(0.91)
GVD^{250}	-0.216***					
	(-3.07)					
GVD_{OLD}		-0.183**	-0.102			
		(-2.24)	(-1.37)			
GVD_{NEW}		-0.285***		-0.204***		-0.267***
		(-4.00)		(-3.10)		(-4.16)
LNSMB12					0.029*	0.045***
					(1.73)	(2.66)
R^2	6.3%	7.0%	1.3%	3.3%	1.5%	6.7%
N	260	260	260	260	260	260

Table 5: Cyclical variations in GVD

Panel A examines whether GVDs forecasting ability for market excess returns (MKTRF) and real Non Residential Private Fixed Investment growth (PFIG) is stronger during periods of low GDP growth. LowGDP is a dummy equal 1 if this quarter's GDP growth is below its full-sample time-series median. We predict the next quarter's MKTRF and INV using GVD and an interaction between GVD and LowGDP. Panel B examines whether GVD's ability to predict quarterly and annual INV is related to time-variation in risk premia. We decompose GVD into two components:

$$GVD_{t-11,t} = a + b\ Mktrf_{t+1,t+q} + u_t$$

where q=3 (12) in quarterly (annual) specifications. GVDP is the predicted value of GVD and GVDR is the residual. We also predict the market risk premium:

$$Mktrf_{t+1,t+q} = a + b\ CAY_t + c\ CAPE_t + d\ IK_t + v_t$$

MKTP is the predicted market risk premium and MKTR is the residual. Panel B examines whether GVDP, GVDR, MKTP, and MKTR predict quarterly and annual PFIG. All standard errors are Newey-West (with 3 lags). The symbols ***, **, and * represent statistical significance at the 1%, 5% and 10% levels, respectively. T-statistics are in parentheses.

Panel A: Forecasting with GDP growth interaction

	MKTRF	PFIG
Intercept	0.027***	0.013***
	(3.52)	(4.32)
GVD	0.264	-0.166**
	(1.29)	(-2.18)
GVD*LowGDP	1.113***	-0.302**
	(2.99)	(-2.10)
Low GDP	0.013	-0.020***
	(1.05)	(-4.26)
R^2	6.2%	15.6%
N	258	259

Panel B: Risk premia and investment growth

	Quarterly			Annual		
	(1)	(2)	(3)	(1)	(2)	(3)
Intercept	0.009	0.012***	0.006	0.047	0.021	-0.005
	(0.71)	(4.42)	(1.64)	(1.17)	(1.45)	(-0.24)
GVDP	-0.068			0.458		
	(-0.13)			(0.29)		
GVDR	-0.222***			-1.135***		
	(-3.01)			(-3.53)		
MKTP		-0.045	-0.025		0.207*	0.236**
		(-0.56)	(-0.31)		(1.66)	(2.00)
MKTR		-0.008	0.008		-0.065	-0.013
		(-0.33)	(0.33)		(-1.16)	(-0.25)
GVD			-0.201**			-1.007***
			(-2.60)			(-2.75)
Rsquare	6.4%	0.2%	6.3%	10.5%	5.2%	16.2%
N	259	239	239	253	236	236

Table 6: Predicting returns and investments of size sorted portfolios

This table presents results of predicting quarterly excess returns (Panel A) and annual investment growth (Panel B) for 10 size sorted portfolios using GVD. Portfolios are formed based on NYSE size breakpoints. Investment is annual capital expenditure from January to December, and the sample for investment growth is restricted to firms with fiscal year ending in December. GVDP and GVDR are defined as in Table 5. All standard errors are Newey-West (with 3 lags). T-statistics are in parentheses.

Panel A: Quarterly non-overlapping returns (1926-2011)

	Small	2	3	4	5	6	7	8	9	Big	Sm- Big
Specification 1											
Intercept	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07
	(3.28)	(3.28)	(3.28)	(3.28)	(3.28)	(3.28)	(3.28)	(3.28)	(3.28)	(3.28)	(3.28)
GVD	1.17	1.13	1.12	1.07	1.07	0.91	0.95	0.86	0.80	0.69	0.49
	(2.64)	(3.04)	(3.22)	(3.43)	(3.61)	(3.27)	(3.66)	(3.53)	(3.51)	(3.67)	(1.49)
Rsquare	1.5%	1.9%	2.2%	2.7%	2.7%	2.5%	3.2%	3.1%	2.9%	3.2%	0.5%
N	341	341	341	341	341	341	341	341	341	341	341
Specification 2											
Intercept	1.12	0.99	0.95	0.84	0.83	0.77	0.72	0.66	0.64	0.52	0.60
	(6.86)	(7.66)	(7.92)	(10.51)	(9.89)	(13.07)	(20.97)	(30.87)	(33.92)	(62.62)	(3.75)
GVDP	44.98	39.93	38.02	33.61	33.54	30.90	28.78	26.60	25.56	20.93	24.05
	(6.78)	(7.57)	(7.83)	(10.35)	(9.75)	(12.86)	(20.66)	(30.92)	(33.52)	(62.08)	(3.69)
GVDR	-0.31	-0.18	-0.13	-0.04	-0.03	-0.10	0.01	-0.02	-0.05	-0.01	-0.31
	(-1.20)	(-0.91)	(-0.75)	(-0.25)	(-0.26)	(-0.99)	(0.08)	(-0.23)	(-1.08)	(-0.18)	(-1.07)
Rsquare	71.7%	78.5%	83.0%	85.9%	88.0%	90.9%	94.1%	95.5%	97.2%	97.6%	38.7%
N	340	340	340	340	340	340	340	340	340	340	340

Panel B: Annual non-overlapping CAPEX growth (1974-2011)

	Small	2	3	4	5	6	7	8	9	Big	Sm- Big
Specification 1											
Intercept	-0.16	-0.07	-0.009	-0.028	-0.004	-0.004	0.006	0.03	0.025	0.05	0.21
	(-3.85)	(-1.86)	(-0.19)	(-0.81)	(-0.22)	(-0.14)	(0.30)	(1.78)	(1.10)	(2.77)	(7.36)
GVD	-2.49	-1.67	-1.46	-1.27	-1.28	-0.96	-0.82	-0.58	-0.48	0.09	-2.59
	(-2.28)	(-1.72)	(-1.26)	(-1.37)	(-1.76)	(-1.94)	(-1.86)	(-2.22)	(-1.01)	(0.20)	(-3.12)
Rsquare	11.0%	5.6%	4.2%	5.1%	6.5%	3.9%	4.3%	3.4%	1.6%	0.1%	19.2%
N	38	38	38	38	38	38	38	38	38	38	38
Specification 2											
Intercept	-0.11	-0.04	0.04	-0.03	-0.05	-0.06	-0.14	-0.02	-0.08	0.00	0.11
	(-0.36)	(-0.12)	(0.15)	(-0.12)	(-0.28)	(-0.33)	(-0.92)	(-0.23)	(-0.54)	(0.01)	(0.47)
GVDP	-0.23	-0.30	0.73	-1.06	-2.94	-3.31	-6.72	-2.56	-4.55	-1.93	-1.69
	(-0.02)	(-0.02)	-0.06	(-0.11)	(-0.40)	(-0.42)	(-1.09)	(-0.77)	(-0.81)	(-0.44)	(-0.17)
GVDR	-2.68	-1.83	-1.66	-1.41	-1.38	-0.88	-0.69	-0.60	-0.417	0.132	2.82
	(-2.90)	(-2.49)	(-1.77)	(-1.72)	(-2.00)	(-1.86)	(-1.76)	(-2.40)	(-0.96)	(0.32)	(4.08)
Rsquare	11.7%	6.3%	5.0%	6.0%	8.1%	4.3%	9.0%	5.1%	4.2%	0.6%	20.6%
N	37	37	37	37	37	37	37	37	37	37	37

Table 7: Multivariate prediction

This table presents results of multivariate regressions that predict the quarterly equity premium (excess returns of the value-weighted market index over the Treasury bill rate), and quarterly real private non-residential fixed investment growth, with GVD^{250} and our set of benchmark predictors. The benchmark predictors are interest rate variables, DS and TS (default and term spreads); valuation ratios, DP, CAPE, BM, CRSPNPY (dividend to price, cyclically adjusted price to earnings, book-to-market of the DJIA, and log net payout of all CRSP stocks); macro variables, CAY and IK (consumption-wealth ratio and investment-to-capital ratio). We also include one lag of each right hand side variable. KS refers to 'kitchen-sink' regressions that include all available risk premium predictors. KS-1 includes all variables available from 1926 and KS-2 includes all variables from 1952 (since the start of the availability of quarterly CAY). The table also reports the start and end dates for the dependent variable in each regression. The symbols ***, **, and * represent statistical significance at the 1%, 5% and 10% levels, respectively. T-statistics are in parentheses.

Panel A: Predicting quarterly non-overlapping market returns

	Lags	Interest Rate	Valuation	Macro	KS-1	KS-2
Intercept	0.034***	0.011	-0.099	0.163***	-0.114	0.102
	(4.36)	(0.58)	(-0.64)	(3.22)	(-0.73)	(0.58)
GVD^{250}	0.665***	0.721***	0.645***	0.617***	0.671***	0.669***
	(3.98)	(3.89)	(3.21)	(3.49)	(3.42)	(3.92)
L.MKT	0.084					0.071
	(1.27)					(1.04)
L.PFIG	-0.167					-0.086
	(-0.77)					(-0.31)
TS		0.396			0.977*	0.828*
		(0.79)			(1.65)	(1.79)
DS		1.673			-0.111	0.376
		(0.77)			(-0.06)	(0.18)
NPY			0.039		0.025	-0.025
			(0.88)		(0.56)	(-0.48)
CAPE			0.001		0.002	0.003
			(0.28)		(0.71)	(0.95)
DP			0.126		0.141	0.079
			(1.28)		(1.56)	(1.21)
BM			-0.038		-0.021	0.032
			(-0.92)		(-0.50)	(0.55)
CAY				0.682**		0.602
				(2.26)		(1.48)
IK				-3.692***		-3.489
				(-2.64)		(-1.50)
R^2	0.064	0.049	0.070	0.099	0.081	0.128
N	258	340	336	239	336	236
Start date	1947:3	1927:1	1927:2	1952:2	1927:2	1952:2
End date	2011:4	2011:4	2010:4	2011:4	2010:4	2010:4

Table 7: Multivariate prediction (contd.)

Panel B: Predicting quarterly non-overlapping investment growth

	Lags	Interest Rate	Valuation	Macro	KS-1	KS-2
Intercept	0.002	0.023***	0.053	0.001	-0.029	-0.014
	(1.06)	(5.11)	(1.05)	(0.03)	(-0.58)	(-0.30)
GVD^{250}	-0.135***	-0.213***	-0.243***	-0.199***	-0.196***	-0.117**
	(-2.83)	(-3.09)	(-3.67)	(-2.83)	(-2.70)	(-2.09)
L.MKT	0.042**					0.036**
	(2.54)					(2.54)
L.PFIG	0.427***					0.322**
	(4.62)					(2.56)
TS		0.115			0.124	0.123
		(0.94)			(0.80)	(0.85)
DS		-2.069***			-2.350***	-1.598***
		(-4.97)			(-5.20)	(-3.13)
NPY			0.028		0.016	0.007
			(1.62)		(0.86)	(0.51)
CAPE			0.002**		-0.000	0.000
			(2.27)		(-0.20)	(0.25)
DP			0.007		0.025	0.026*
			(0.34)		(1.41)	(1.67)
BM			0.006		-0.023*	-0.014
			(0.46)		(-1.70)	(-0.93)
CAY				0.025		0.050
				(0.30)		(0.59)
IK				0.156		-0.458
				(0.29)		(-1.02)
R^2	0.255	0.195	0.108	0.063	0.215	0.341
N	259	260	256	239	256	236
Start date	1947:3	1947:3	1947:3	1952:2	1947:3	1952:2
End date	2011:4	2011:4	2010:4	2011:4	2010:4	2010:4

Table 8: Predicting the equity premium using GVD: robustness tests

This table presents results of regressions predicting excess returns of the CRSP value-weighted market index over the 3-month Treasury bill rate with an intercept and GVD. Panel A presents full-sample regressions predicting quarterly, non-overlapping excess market returns with GVD^{250} and includes specifications with OLS, Newey-West, and Stambaugh bias-corrected standard errors. The Stambaugh correction is done using the method in Amihud and Hurvich (2004). Panel B shows results of these regressions for three approximately equal sub-samples, 1927:1-1955:2, 1955:3-1983:3, 1983:4-2011:4. All regressions in Panel B are with non-overlapping returns and Stambaugh bias-corrected standard errors. Panel C displays results for monthly market risk premium predictions using all three versions of GVD--GVD^{250}, GVD^{Median}, GVD^{Credit}. Panel D displays the results of additional robustness tests. 'NEWEX dum' controls for the creation of the NASDAQ and the AMEX by including a dummy variable NEWEX equal to one in the first year of each of these exchanges, zero otherwise. 'Ex-NEWEX' excludes the two years where NEWEX equals one. 'Ex-Internet' ends the sample in 1996, to exclude the internet period, and 'Ex-1970s' excludes the 1970s, in order to exclude the oil shocks. 'FF' controls for annual returns of the market, HML, and SMB over the past year. 'Skip' skips a quarter between measuring GVD and forecasting market returns. The symbols ***, **, and * represent statistical significance at the 1%, 5% and 10% levels, respectively. T-statistics are in parentheses.

Panel A: Full-sample regressions: OLS, Stambaugh bias corrected, and Newey West (3 lags)

	OLS	OLS-Stam	OLS-NW
Intercept	0.038***	0.038***	0.038***
	(4.67)	(4.86)	(4.15)
GVD^{250}	0.757***	0.742***	0.757***
	(3.37)	(3.30)	(3.74)
R^2	3.3%	3.3%	3.3%
N	340	340	340

Panel B: Sub-samples

	1927:1-1955:2	1955:3-1983:3	1983:4-2011:4
Intercept	0.056***	0.033***	0.029***
	(2.89)	(3.32)	(3.03)
GVD^{250}	1.018	0.780***	0.486*
	(1.43)	(2.74)	(1.92)
R^2	2.5%	6.8%	3.8%
N	114	113	113

Table 8: Predicting the equity premium using GVD: Robustness tests (contd.)

Panel C: Predicting monthly market excess returns with different versions of GVD

	Monthly	Monthly	Monthly
Intercept	0.010***	0.012***	0.006**
	(4.52)	(4.09)	(2.11)
GVD^{250}	0.171***		
	(2.65)		
GVD^{Median}		0.264***	
		(2.94)	
GVD^{Credit}			0.070
			(1.15)
R^2	0.7%	0.9%	0.4%
N	1020	1020	575

Panel D: Robustness to new exchanges, Internet years, 1970s, and Fama-French factors

	NEWEX dum	Ex-NEWEX	Ex-Internet	Ex-1970s	FF	Skip
Intercept	0.038***	0.037***	0.040***	0.039***	0.039***	0.038***
	(4.68)	(4.54)	(4.22)	(4.50)	(4.02)	(4.21)
GVD^{250}	0.787***	0.750***	0.778***	0.748***	0.820***	0.546***
	(3.35)	(3.15)	(2.88)	(2.99)	(3.79)	(3.08)
NEWEX	0.018					
	(0.44)					
MKTRF12					-0.016	
					(-0.28)	
HML12					-0.016	
					(-0.32)	
SMB12					0.050	
					(0.89)	
R^2	3.3%	2.9%	2.9%	2.9%	3.6%	2.9%
N	340	332	281	304	338	339

Table 9: Out-of-sample robustness tests for equity premium prediction

This table presents results of out-of-sample predictions of the market risk premium (excess returns of the value-weighted market index over the treasury bill rate) using GVD^{250} and GVD^{Median}. These are from expanding window estimations, with different start dates for the evaluation period. P-values are for MSE-F tests (McCracken (2007)) of equal predictive ability between using the historical mean market excess return and GVD to forecast the market risk premium. Panel A presents results for quarterly (non-overlapping) predictions. P-values in Panel A are from critical values in McCracken (2007). Panel B presents results for annual predictions (with quarterly overlap). P-values in Panel B are for the MSE-F statistic from a block bootstrap procedure with a block length of four.

Panel A: Quarterly (non-overlapping) market excess returns

Start	GVD^{250}		GVD^{Median}	
	OOS R^2	p-value	OOS R^2	p-value
1947:1	3.9%	<0.01	4.1%	<0.01
1957:1	5.0%	<0.01	4.9%	<0.01
1967:1	6.0%	<0.01	6.6%	<0.01
1977:1	5.5%	<0.01	5.9%	<0.01
1987:1	2.3%	0.05	3.7%	<0.01

Panel B: Annual (with quarterly overlap) market excess returns

Start	GVD^{250}		GVD^{Median}	
	OOS R^2	p-value	OOS R^2	p-value
1947:1	5.3%	<0.01	8.4%	<0.01
1957:1	6.2%	<0.01	9.3%	<0.01
1967:1	9.3%	<0.01	15.2%	<0.01
1977:1	6.8%	<0.01	9.7%	<0.01
1987:1	2.1%	0.08	4.2%	0.027

Figure 1: Number of firms in the sample

This figure plots the total number of firms in the CRSP universe over our sample period.

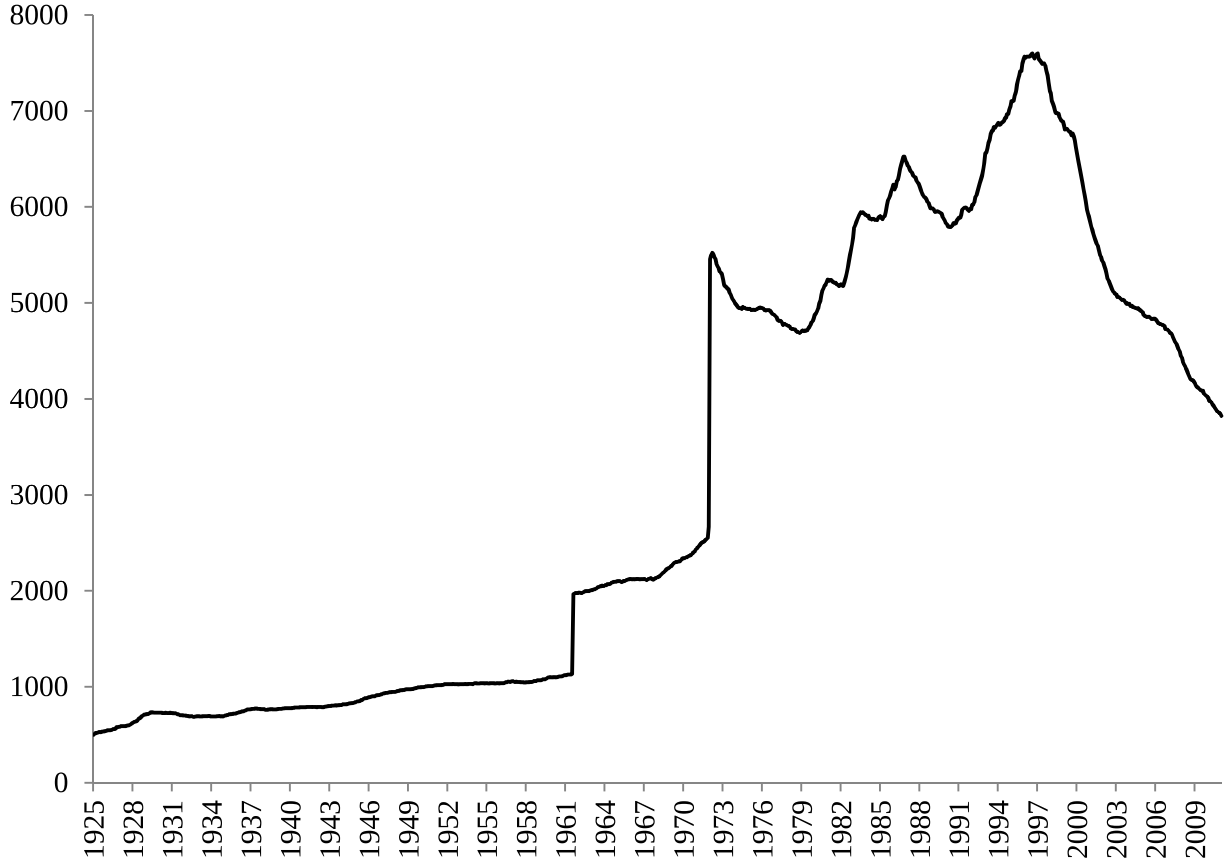


Figure 2: Time series of GVD^{250}

This figure shows the time-series of GVD^{250}, which is the change in the log weight of the top 250 firms in the aggregate market portfolio over the last 12 months. NBER dated recessions are shaded in gray. Local maxima/minima that are not in or near recessions are indicated by text boxes, that include the date corresponding to the maxima/minima, and the proximate financial market-related event. The symbol "*s" indicates that the maxima/minima does not exactly correspond with the date of the event, or that it is difficult to pinpoint an exact date as the event extends for several months. These events are discussed in the text in greater detail.

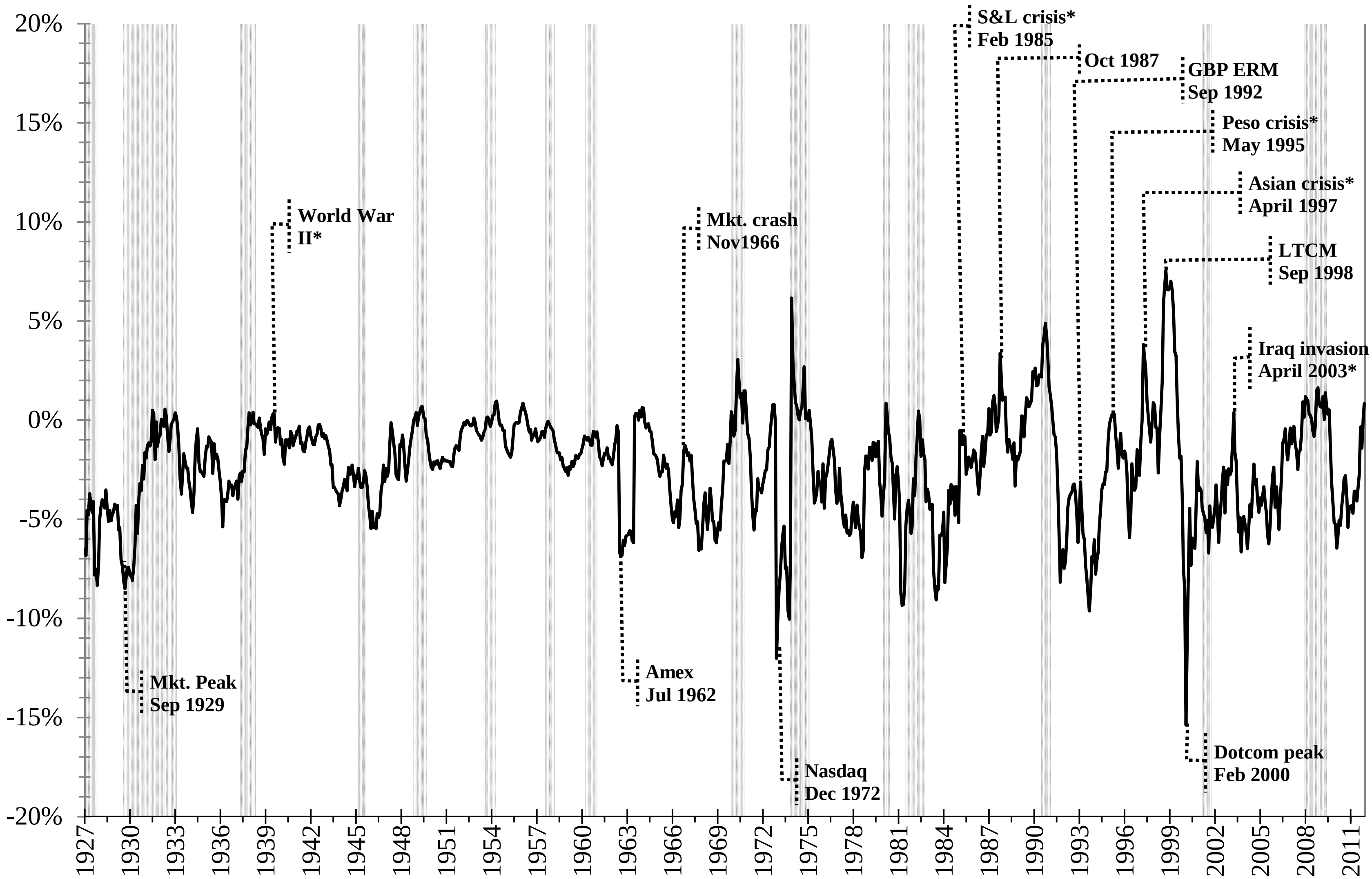
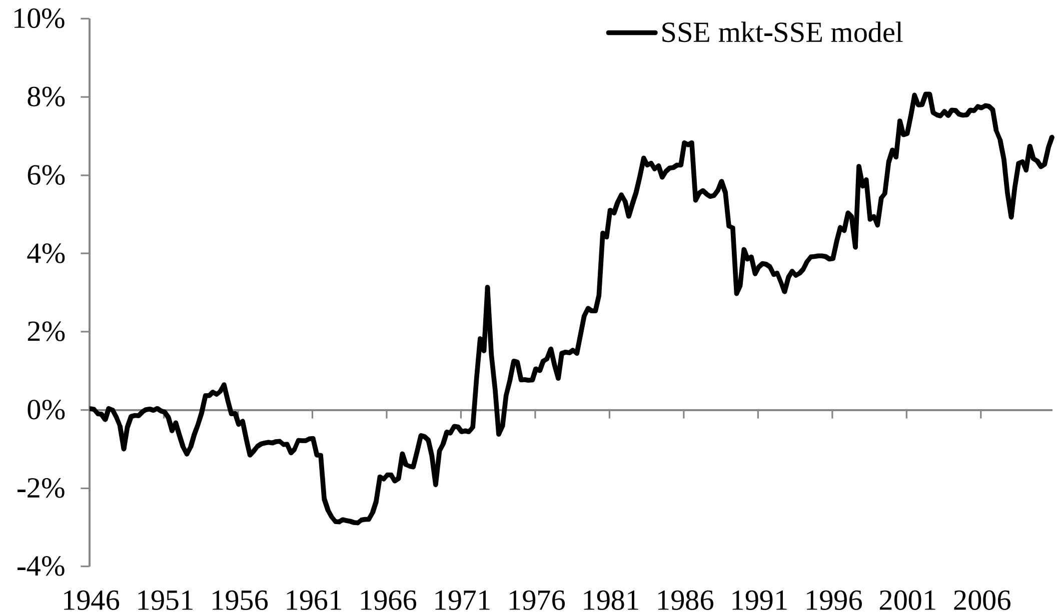


Figure 3: Out-of-sample prediction errors for GVD^{250}

This figure assesses the performance of out-of-sample forecasts of the market risk premium (excess returns of the value-weighted CRSP index over the Treasury bill rate) made with GVD^{250} relative to a simple benchmark, the historical average equity risk premium. The figure plots the difference in cumulative sum of squared errors (SSEs) between forecasts made with GVD^{250} and the historical average equity premium. Both predictions are from expanding window estimation periods, beginning in 1926, with the first estimation window having 20 years of data. Panel A plots differences in SSEs of forecasts of quarterly market excess returns, while Panel B does so for annual market excess returns, with quarterly overlap.

Panel A: Quarterly, non-overlapping prediction errors



Panel B: Annual, with quarterly overlap prediction errors