

Intangible Risk?

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1 Introduction

The large increase in stock prices during the 1990's has prompted substantial discussion in both the popular press and academia. Some observers see the rise in the price of stocks relative to measures of fundamentals, such as the book value of equity, as clear evidence of irrationality on the part of investors. Under this view investors over-reacted to temporary changes in corporate earnings or changes in industrial structure brought on by the internet revolution (see, for example, Shiller (2001)). An alternative view is that the book value of assets or equity are poor measures of fundamentals in a world where investment is shifting towards more intangible forms of capital. A forceful example of this argument is set forth by Hall (2001). Hall uses the difference between measures of physical capital and security market prices to infer a measure of intangibles. Hall argues that during the 1990's firms undertook substantial investment in intangible capital which was understood by the market and which resulted in a large difference between the book and market values of capital.

Differences in the book and market values of equity capital can also be found across firms. Figure 1 plots the market value relative to book value of 5 portfolios of US stocks over the period 1950 to 2000. The portfolios were constructed based on the market and book values of the underlying stocks. This construction imitates Fama and French (1992) and is described in section 2. Portfolio constructions such as this have attracted considerable attention in the finance literature because the resulting portfolios have different mean returns. Portfolios with higher market-to-book values have lower average returns, and the challenge to financial economists is to explain this difference. Competing explanations pervade the empirical finance literature including alternative risk exposure or irrationality in financial markets.¹ We explore these findings because the cross-sectional differences in figure 1 may reflect differences in intangible investments. To use asset market data to measure intangible capital requires the differences in mean returns be accounted for by the resulting differences in risk exposure.

¹Examples of these views are found in Fama and French (1992), Chan, Lakonishok, and Sougiannis (1999) and Bansal, Dittmar, and Lundblad (2002)

If intangible investment is to be an explanation of the difference between market and book values of firms it should be reflected in future cash flows. Market values should be the present value of these future cash flows discounted at a rate that reflects the riskiness of the cash flows. Using this argument Bond and Cummins (2000) challenge Hall's view of the market of the 1990's by examining the discounted value of future cash flows as predicted by market analysts. They do not correct for potential differences in risk in their analysis, however.

Our goal in this paper is to examine the time series evidence from portfolios like those of figure 1 to see if the data can support an explanation for differences between market and book values based on expected future cash flows and risk adjustments. We present time series evidence about the longer-run properties of cash flows to several portfolios. Differences in intangible investment may be identified by either industry structure, R&D expenditures or market-to-book values directly. This essay follows the finance literature by examining evidence based on market-to-book differences. As we will see, the constructed portfolios with high market-to-book ratios include firms that invest more in R&D. Comparable analyses can be done of industry-based portfolios. We decompose risk exposure by frequency to explore whether high market-to-book firms are exposed to different economic risk than other firms. We use to either consumption or a proxy for the risk faced by stockholders as in Heaton and Lucas (2000).

While much of the finance literature focuses on finding risk adjustments for short-term returns, we also consider cash flow risk and its decomposition by frequencies. Risk adjustment for high frequencies may be undermined by transaction costs or other adjustment costs that investors must confront.² In contrast, prospects about long-run growth potential may dominate asset valuation of cash flows and provide an important source of risk in the economy. In particular two recent papers, Bansal, Dittmar, and Lundblad (2002) and Cohen, Polk, and Vuolteenaho (2002) have claimed empirical success in explaining differences in market-to-book values based on long-run measures of risk in cash flows. We expand on this

²See Daniel and Marshall (1997) for a discussion of this.

work and confront the treacherous measurement problem of quantifying long-horizon risk. We study whether the market-to-book portfolios isolate cash flows with heterogeneous risk exposure. We ask whether the risk attributed to portfolios with an arguably large amount of intangible capital looks different than other capital market risk?

2 Portfolio Analysis and Data Description

We start our empirical investigation by revisiting an analysis of Fama and French (1992) and (1995). Fama and French form portfolios based on the ratio of book equity-to-market equity (BE/ME), and estimate the mean return of these groups. They find that low BE/ME have high average returns. Fama and French (1992) view a low BE/ME as signalling sustained high earnings and/or low risk. Equivalently, this low BE/ME can be viewed as evidence for the importance of intangible capital consistent with the argument of Hall (2001). Neither book equity nor market equity measure the entire capital stock because capital financed by bond holders is excluded.

While we follow Fama and French (1992) in constructing portfolios ranked by BE/ME ratios, We use a coarser sort than they do. We focus on five portfolios instead of ten. Each year listed firms are ranked by their BE/ME using information from Compustat. Firms are then allocated into five portfolios and this allocation is held fixed over the following year. The weight placed on a firm in a portfolio is proportional to its market value each month.³ Firms may change groups over time and the value weights are adjusted accordingly. In effect the BE/ME categories are used to form five portfolio dividends, returns and values each time period. This grouping is of course different in nature than the grouping of firms by industry SEC codes, an approach commonly used in the IO literature. For instance firms in the low BE/ME category may come from different industries and the composition may change through time. On the other hand this portfolio formation may successfully identify interesting payout heterogeneity at the firm level.

As proxies for cash flows to holding these portfolios, we construct two alternative mea-

³See Fama and French (1992) for a more complete description of portfolio construction.

asures. The first measure is based on dividends imputed from the Center for Research in Securities Prices (CRSP) return files. Each month and for each stock CRSP reports a return without dividends, denoted $R_{t+1}^{wo} \equiv P_{t+1}/P_t$ and a total return that includes dividends, denoted $R_{t+1}^w \equiv (P_{t+1} + D_{t+1})/P_t$. The dividends yield D_{t+1}/P_t is then imputed as:

$$D_{t+1}/P_t = R_{t+1}^w - R_{t+1}^{wo} .$$

Changes in this yield along with the capital gain in the portfolio are used to impute the growth in portfolio dividends. This construction of dividends has the interpretation of following a initial investment of \$1 in the portfolio and extracting the dividends while reinvesting the capital gains. From the monthly dividend series we compute quarterly averages. We further average the dividends over a year because of the pronounced seasonality in dividend payouts by firms. Finally real dividends are constructed by normalizing nominal dividends by the implicit price deflator for nondurable and service consumption take from the National Income and Product accounts.

At the time of the conference we will also present evidence based on a second measure of dividends that makes use of information from the income statements and balance sheets of firms as reported in Compustat. We follow Vuolteenaho (2002) and Cohen, Polk, and Vuolteenaho (2002) and construct “clean-surplus” earnings as the change in book equity plus dividends as described above. This alternative measure accounts for the potential of retained earnings that are not paid out as dividends. To construct an approximate growth rate for these dividends we normalize by the initial level of book equity so that the growth series is for an initial \$1 investment in book equity. We exclude any firms where the implied level of cash flows are less than book equity. This allows us to consider and model the logarithm of the (gross) growth series.⁴

Table 1 reports some sample statistics for our portfolios and for the CRSP value-weighted

⁴We have also constructed a measure of cash flows as in Fama and French (1999) that considers net cash paid out by the firm. This measure corresponds to the variable considered by Hall (2001) at the aggregate level. A difficulty with this measure is that it is negative quite frequently which makes times series modeling of growth somewhat more challenging. In future drafts we plan in to consider this measure.

return on the NYSE, AMEX and NASDAQ. Notice that the portfolios with lower BM/ME (high market value relative to book value of equity) are also the ones with the highest level of R&D relative to sales. This is potentially consistent with the idea that large R&D expenditures will ultimately generate high cash flows in the future thus justifying high current market values. These same portfolios have lower average (log) dividend growth. It should be noted that the dividends are sufficiently volatile, however and the growth rates sufficiently small that growth rate differences, if they exist, are very hard to identify from these data. As a result it is difficult to make precise predictions about the level of dividends very far in the future. Since long-run cash flows dominate any calculation of market values, these implied values are somewhat uncertain.

The five BE/ME portfolios imply different risk-return tradeoffs. As in Fama and French (1992), the low BE/ME portfolios have lower mean returns but not substantially different volatility than high BE/ME portfolios. This results in a much higher Sharpe Ratio for the high BE/ME portfolio. Notice that this ratio is higher than that of the market portfolio implying that the market portfolio is not mean variance efficient. This observation can be made much more dramatic by taking a long position in the high BE/ME portfolio offset by a short position in the low BE/ME portfolio.

Results such as these have generated substantial debate in the literature between those who interpret the return differential as reflecting risk and those who view the large Sharpe ratios as not reasonable and clearly evidence of substantial mispricing. For example Fama and French (1992) argue that differentials in returns represent an important risk factor not captured in the market portfolio. They construct an alternative to the market portfolio to use in pricing. This alternative is combines a long position in the low ME/BE portfolio, a short position in the High ME/BE portfolio along with other positions. While such a benchmark can always be constructed *ex post* (see, for example, Hansen and Richard (1987)) this analysis is deemed successful because of its ability to price a large cross-section of portfolios. Unfortunately it is not clear what economic risk being priced in their benchmark security (see, for example, Lakonishok, Shleifer, and Vishny (1994)). For this reason in what

follows we study the evolution of the implied dividend series and how they covary with some potentially meaningful measures of economic risk.

3 Decomposing Dividend Variation

The dividend processes may display different persistence patterns. We explore these differences by examining spectral decompositions of the dividend growth processes. Dividend processes are known to have pronounced seasonality, but we will focus on lower frequency movements.

Figure 2 reports the spectral densities for dividend growth processes. Since they are computed in terms of growth rates, the peak effect is away from zero frequencies and in the range of business cycles. There are some differences. Low BE/ME portfolios show more sensitivity to business cycle frequencies, although the peak business cycle response is actually in the second portfolio. Such comparisons should be qualified because of the difficulty in estimating these spectra accurately.

The spectral densities for the two consumption growth processes are also reported in figure 2. They are smoother across frequencies, as expected from permanent income theory.

4 Risk Decomposition

We consider several decompositions of dividend risk. Since we are not finding arbitrage among the dividend and return processes, we know that we can always produce descriptive models that the price correctly the dividend processes. Factor characterizations of prices seek to accomplish this in low-dimensional ways, but often without producing an interpretable model of the implied risk premia. Thus while a relatively unstructured observable factor approach can yield empirically interesting characterizations, essentially the same finding can be embraced as a challenge to standard decision-making models under rational expectations.

Our empirical analysis is instead motivated by recent claims by Bansal, Dittmar, and Lundblad (2002) that a) there are important empirical differences in the temporal depen-

dence of dividends and cash flows; b) there is a role for consumption in understanding risk adjustments based on long run growth considerations in payoffs to equity holders.

We explore risk as measured by covariation with two alternative measures of consumption. One is a measure of aggregate consumption that is known to give rise to the equity premium puzzle. As a result we will find small implied risk adjustments. The other measure of consumption is based on the idea that participation in asset markets is concentrated among a small proportion of the population. As a rough proxy for consumption we use proprietors' income plus aggregate dividends, which we expect to be more correlated with actual dividend processes. Even under complete market segmentation, this measure can be criticized because it may fail to properly differentiate consumption from savings. Nevertheless, we use it to explore how market segmentation may alter our findings.

4.1 Cointegration

Bansal, Dittmar, and Lundblad (2002) and Bansal and Yaron (2002) use cointegration as a means of measuring long-run risk. They do not restrict the ratio of dividends to consumption (the difference between log dividends and log consumption) to be stationary. Instead they presume that:

$$d_t - \gamma c_t = u_t$$

where the process u is stationary. The stationarity restriction is used to identify γ , and γ is used in turn as a measure of long-run consumption risk encoded in the dividend process. The stationarity restriction can identify γ because both consumption and dividends display growth.

It is unappealing to us to envision cash flow or dividend processes with literally permanent growth dispersions. In our analysis not reported here, we found very little evidence against the hypothesis that $\gamma = 1$ for each of the dividend processes. We also found that γ was not estimated accurately and that point estimates were not robust across methods of estimation.

Bansal, Dittmar, and Lundblad (2002) extend this notion of cointegration by introduc-

ing time trends into cointegrating regressions. They allow for the process $\{d_t - \gamma c_t\}$ to be stationary about a linear trend. With such a specification, they attribute the mean return differences among BE/ME and other portfolios to differences in the γ 's. Low BE/ME portfolios have lower mean returns because their implied dividend processes have long-run negative covariation with consumption. Cointegration estimation with a time trend is, unfortunately, even more problematic than cointegration without a time trend because differences in deterministic growth rates cannot be used to assist in the identification of γ . In practice, there is an extreme correlation between the estimate of γ and the additional coefficient on the time trend. Separating out two sources of growth differences, even if they exist, presents a major challenge for measurement.

While a model with permanent growth dispersion in dividends or cash flows may be unappealing, low frequency differences in cash flow might well have important consequences for valuation and pricing. Even misspecified cointegration measurements may uncover interesting differences in the long run risk across portfolios. Dividend/consumption ratios may be stationary in the long-run, but there may still be a substantial low frequency component in this ratio. Unfortunately, we found the estimation of cointegrating coefficients to yield fragile results. Instead we explore two other approaches, the first of which is similar to another method implemented by Bansal, Dittmar, and Lundblad (2002).

4.2 Dividend Beta

Bansal, Dittmar, and Lundblad (2002) argue that a good predictor differences in risk across portfolios is given by the long run correlation between consumption and dividend growth. We illustrate this finding by computing “dividend betas” for the alternative B/M portfolios. These “beta’s” are constructed as regression coefficients meant to emphasize longer horizons.

To explore long-run dividend risk, we run regressions based on moving sums of consumption and dividends. Suppose there are long run components in consumption and dividends that are masked by high frequency movements in the time series. By running a running long-run regressions, we may isolate better risk components that co-vary with consumption.

Specifically we construct the partial sums:

$$d_t^\ell = \frac{d_t - d_{t-\ell}}{\sqrt{\ell}}$$

and similarly for consumption. These ℓ period differences in the log levels of dividends are equivalently partial sums of dividend growth scaled by $\sqrt{\ell}$. In all cases we remove sample mean growth rates of the respective series. These partial sums scaled appropriately may obey a central limit approximation, which motivates our division by $\sqrt{\ell}$. We perform the analogous construction for our consumption measures and run regressions. These regressions are based on the sample covariance matrix of the scaled partial sums. When the growth rate processes are covariance stationary and only weakly dependent, there is a population counterpart to setting $\ell = \infty$. We report our results in Table 2.

To relate these regression to our spectral decomposition of dividend growth, we compute the so-called transfer function for the long horizon differences as a function of the one period difference. This transfer function can be used to deduce the implied frequency weighting. Note that

$$h(z) \doteq \frac{1 + z + \dots + z^{\ell-1}}{\sqrt{\ell}} = \frac{1 - z^\ell}{\sqrt{\ell}(1 - z)} .$$

To measure the relative importance of frequencies, we form the square modulus for values of $z = \exp(i\omega)$ on the unit circle of the complex plane:

$$\tilde{h}(\omega) = |h[\exp(i\omega)]|^2 = \frac{1 - \cos(\ell\omega)}{\ell[1 - \cos(\omega)]}$$

for $\omega \neq 0$. The limit as ω converges to zero is ℓ . The resulting functions \tilde{h} are reported in figure 3 for different choices of ℓ . These functions have a zero at: $\omega = \frac{2\pi}{\ell}$ with a periodicity equal to ℓ . The first and primary lobe of \tilde{h} is to the left of the frequency corresponding to the period ℓ used in constructing the partial sums. The side lobes are quite small. This figures make operational the link between the length of the partial sum and implied frequencies that

receive emphasis in the calculation of regression coefficients.

Table 2 finds qualitative results that support Bansal, Dittmar, and Lundblad (2002). Dividends on small BE/ME portfolios are negatively related to long-run consumption growth made operational here through the choice of $\ell = 20$. This negative relation with consumption is then consistent with the finding of a small mean return for this B/M portfolio. While the regression coefficients at say lag $\ell = 20$ are not monotone increasing (portfolio three has the largest coefficient), they appear to have some explanatory power.

This success of a long-run adjustment for risk is illusive, however. For instance, the R^2 of some of these regressions are tiny, and measurements are likely to have little meaning. While the regression R^2 are higher for proprietary consumption, they consistently have the wrong pattern to explain average returns. The low BE/ME portfolios also have relatively low regression coefficients.

4.3 VAR Analysis

Finally, we explore an alternative way to characterize the riskiness of the cash flows and dividend series based on standard vector autoregressive (VAR) methods. We will estimate the one-period evolution of consumption dividends and extrapolate this to longer time periods.⁵

Consider the following VAR decomposition of the data. Let d_t denote the logarithm of dividends. Let $c_t - c_{t-1}$ denote the growth rate in consumption expressed as a logarithmic difference. We will use the two alternative measures of consumption described previously. Stack consumption growth and $d_t - c_t$ into the vector y_t and consider the autoregression:

$$A(L)y_t = \gamma + \Gamma w_t$$

where $Ew_t w_t' = I$. We restrict the matrix Γ to be lower triangular. The first component of w_t has an immediate impact on consumption, but the second one does not. This allows us to identify Γ from a covariance decomposition of one-step ahead forecast errors. We call the

⁵The danger in using this method is that a good approximating model for short forecast intervals may miss important long run components.

first shock the consumption innovation.

For risk considerations, our interest is in the response of dividends to a consumption innovation. We are particularly interested in this to ascertain whether the dividend processes provide any form of consumption insurance for low BE/ME portfolios. Thus we compute the power series:

$$B(z) = A(z)^{-1}\Gamma = \sum_{j=0}^{\infty} b_j(z)^j .$$

The sequence of $(2, 1)$ entries of b_j for each j gives us the dividend relative to consumption response and the sequence of $(1, 1)$ entries gives us the response of consumption growth to that same shock. We have imposed a unit root in the dynamical system, and the responses of interest are accumulated accordingly. Specifically, the vector of impulse responses of dividends at date $t + j$ to a shock at date t is:

$$\begin{bmatrix} -1 & 1 \end{bmatrix} \sum_{\ell=0}^j b_{\ell}$$

where the first one is the response to a consumption innovation.

Figure 4 reports the responses of each of the dividend processes to a consumption innovation and Figure 5 the responses to the second “dividend” shock, which is orthogonal to the consumption shock. To conserve on parameters in estimation, we fit five different bivariate VAR systems, one for each dividend process.

Both of these figures use aggregate consumption as the consumption measure. The first three dividend processes are more responsive to a consumption shock than processes four and five. The dividend processes for three lowest BE/ME portfolios, and in particular portfolio two, have peak responses at ten quarters. Business cycle fluctuations may well be more pronounced for the dividend processes of low BE/ME portfolios.

Figures 4 and 5 show that most the dividend variation for the fourth and fifth BE/ME portfolios are captured by dividend shocks. These results suggest that risk corrections will

be more important for the low BE/ME portfolios. On the other hand, they do not uncover a negative longer-run covariation for the BE/ME portfolios as suggested by Bansal, Dittmar, and Lundblad (2002) in their analysis using estimated cointegrating coefficients. While risk adjustments should be more germane for low BE/ME portfolios, we are left without a simple explanation for why the expected returns should be relatively low. We find no evidence that these portfolios provide consumption insurance even for longer horizons.

The aggregate consumption impulse response functions are smooth and muted as expected. While not constrained to be the same, the consumption response to its own innovation is essentially the same for all of the dividend processes. Consumption does not respond to the dividend shocks orthogonal to consumption. Thus the VAR systems are triangular. Consumption Granger-causes dividends but dividends do not Granger-cause consumption. This is to be expected from what we know about aggregate consumption and the permanent income model.

Figures 6 and 7 provide analogous results using our more limited proprietors' measure of consumption. The response patterns of dividends to a consumption innovation are similar to those in Figure 4 except that there is more long-run risk because consumption is more volatile at all horizons. As a consequence, long run covariation between consumption and dividends is more pronounced. The overall differences across dividend responses are less pronounced making observed differences in mean returns more puzzling.

5 Extensions

Our focus in this analysis has been on understanding the dynamics of dividends implied by CRSP returns. Aggregate dividend evidence is used by Shiller (2001) and others to dismiss market efficiency. Hall (2001) argues that dividends are a misleading measure of cash flows in periods of changing dividend payout policies and as measures of total cash flows to capital. Perhaps our anomalous results for dividends will be overturned by a broader measure of cash flows. Consistent with Hall's results our second measures of cash flows to equity holders appear to have different dynamic patterns than do dividends. For example, figure 8 plots

the logarithm of these cash flows relative to lagged book values for each of the portfolios. It remains to characterize the risk in these cash flows.

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Table 1: Properties of Portfolios Sorted by Book-to-Market Value

Portfolios formed by sorting portfolios into 5 portfolios using NYSE breakpoints from Fama and French (1993). Portfolios are ordered from lowest to highest average book-to-market value. Data from 1964 Q3 to 2001. Average return and standard deviation are quarterly averages of the level return. Average dividend growth and standard deviation are of the logarithm of the dividend growth computed from CRSP returns. Average book-to-market are averaged portfolio book-to-market or the period computed from Compustat. Average R&D/Sales also computed from Compustat. The Sharpe Ratio is quarterly. Average P/D is 12 time the average monthly price dividend ratio constructed using CRSP data.

	Portfolio					Market
	1	2	3	4	5	
Avg. Return	1.93%	2.07%	2.35%	2.48%	3.04%	2.04%
Std. Return	9.88%	8.81%	7.97%	7.72%	8.53%	8.53%
Avg. (log) Div. Growth	0.27%	0.20%	0.68%	0.69%	0.97%	0.17%
Std. (log) Div. Growth	5.54%	7.12%	4.40%	4.42%%	7.37%	1.97%
Avg. B/M	0.27	0.58	0.8193	1.11	3.00	1.20
Avg. R&D/Sales	1.27	0.45	0.18	0.12	0.10	0.56
Sharpe Ratio	0.23	0.29	0.38	0.42	0.50	0.29
Avg. P/D	72.04	46.69	39.08	31.53	29.11	42.24

Table 2: Long Horizon Regressions of Dividends On Consumption

Horizon (quarters)	Portfolio				
	1	2	3	4	5
<i>Panel A: Aggregate Consumption</i>					
$\ell = 4$	2.44	3.86	3.45	1.19	-1.75
$\ell = 8$	2.25	4.29	4.09	1.19	-1.95
$\ell = 12$	0.52	2.51	3.74	0.99	-0.57
$\ell = 16$	-0.24	0.77	3.99	1.40	0.99
$\ell = 20$	-1.20	-0.24	4.10	1.63	1.76
<i>Panel B: Proprietors' Consumption</i>					
$\ell = 4$	0.96	0.80	0.54	-0.34	-0.98
$\ell = 8$	1.18	1.02	0.57	-0.38	-1.16
$\ell = 12$	1.36	1.06	0.48	-0.47	-1.05
$\ell = 16$	1.66	1.02	0.47	-0.60	-0.94
$\ell = 20$	1.81	1.03	0.46	-0.73	-0.77

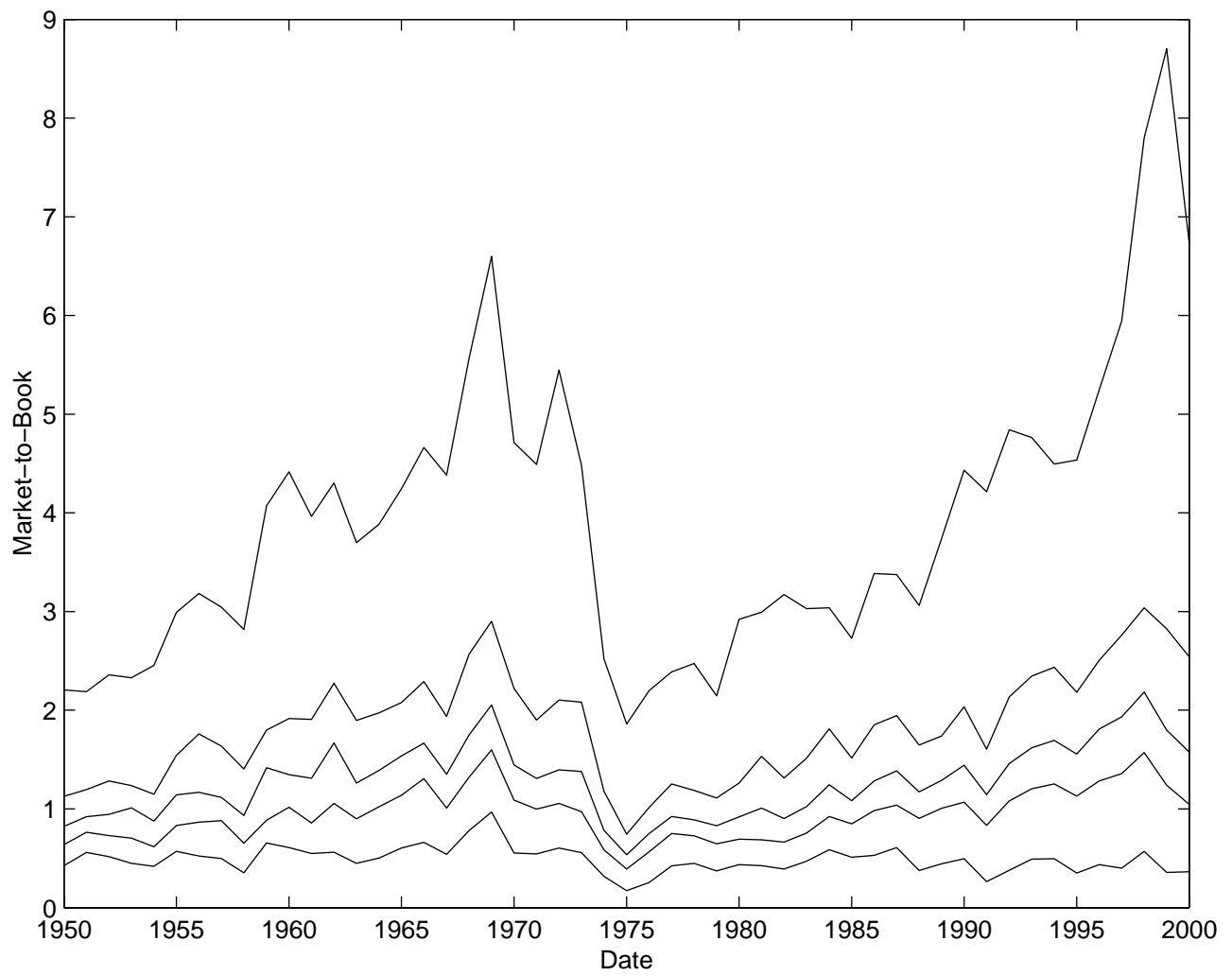


Figure 1: Market-to-Book value of equity for 5 portfolios of stocks

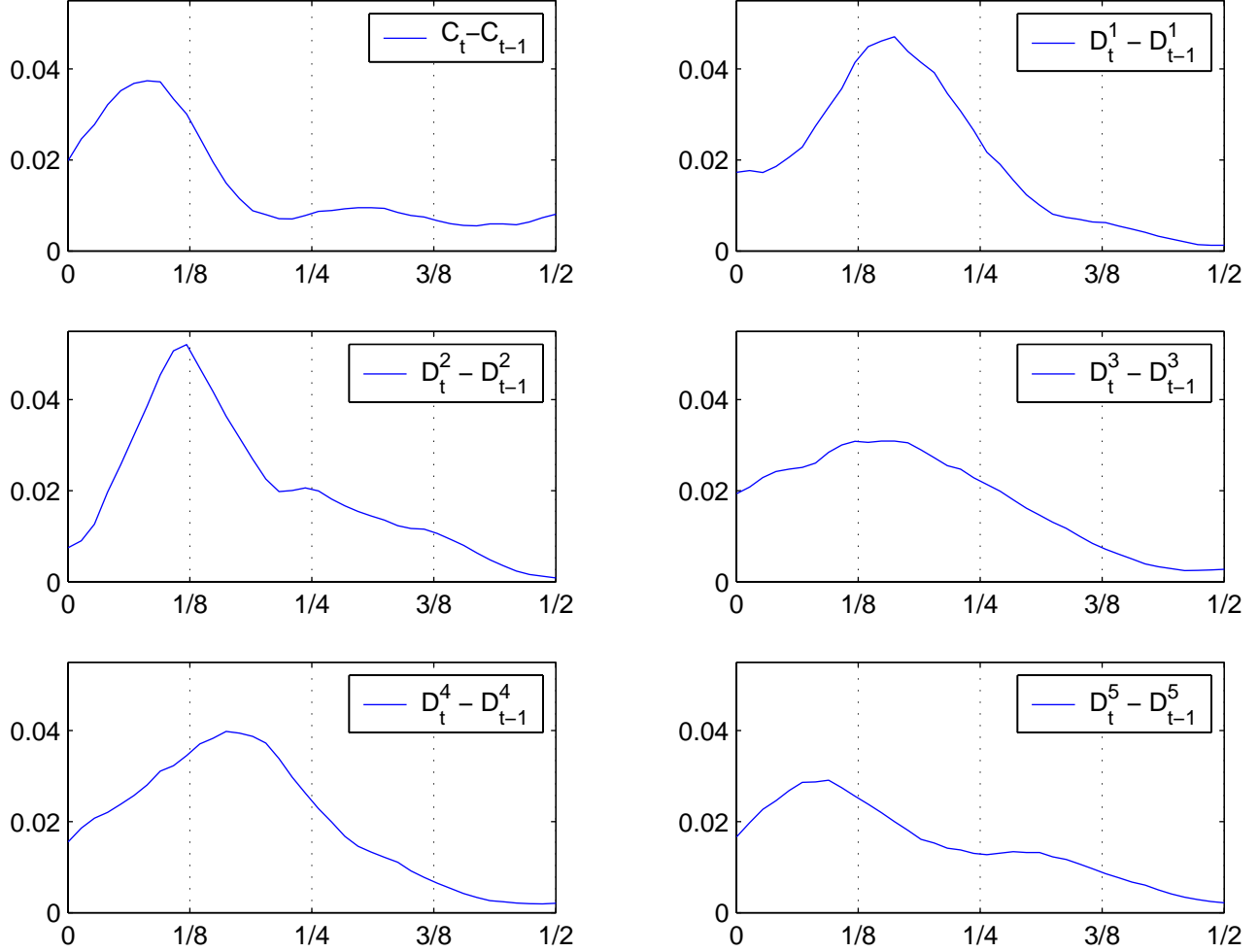


Figure 2: Spectral Density Functions for Dividend and Consumption Growth. This figure contains plots of the spectral density functions for the dividend growth processes associated with the five B/M portfolios and the two consumption growth rates. The spectral densities are rescaled to integrate to unity. The frequencies reported on the horizontal axis are displayed as fraction of $\frac{\pi}{2}$. Seasonal frequencies (frequencies from $(\pi/2, \pi)$) are omitted from the plots. The period (in years) associated with each fraction is the fraction reciprocal.

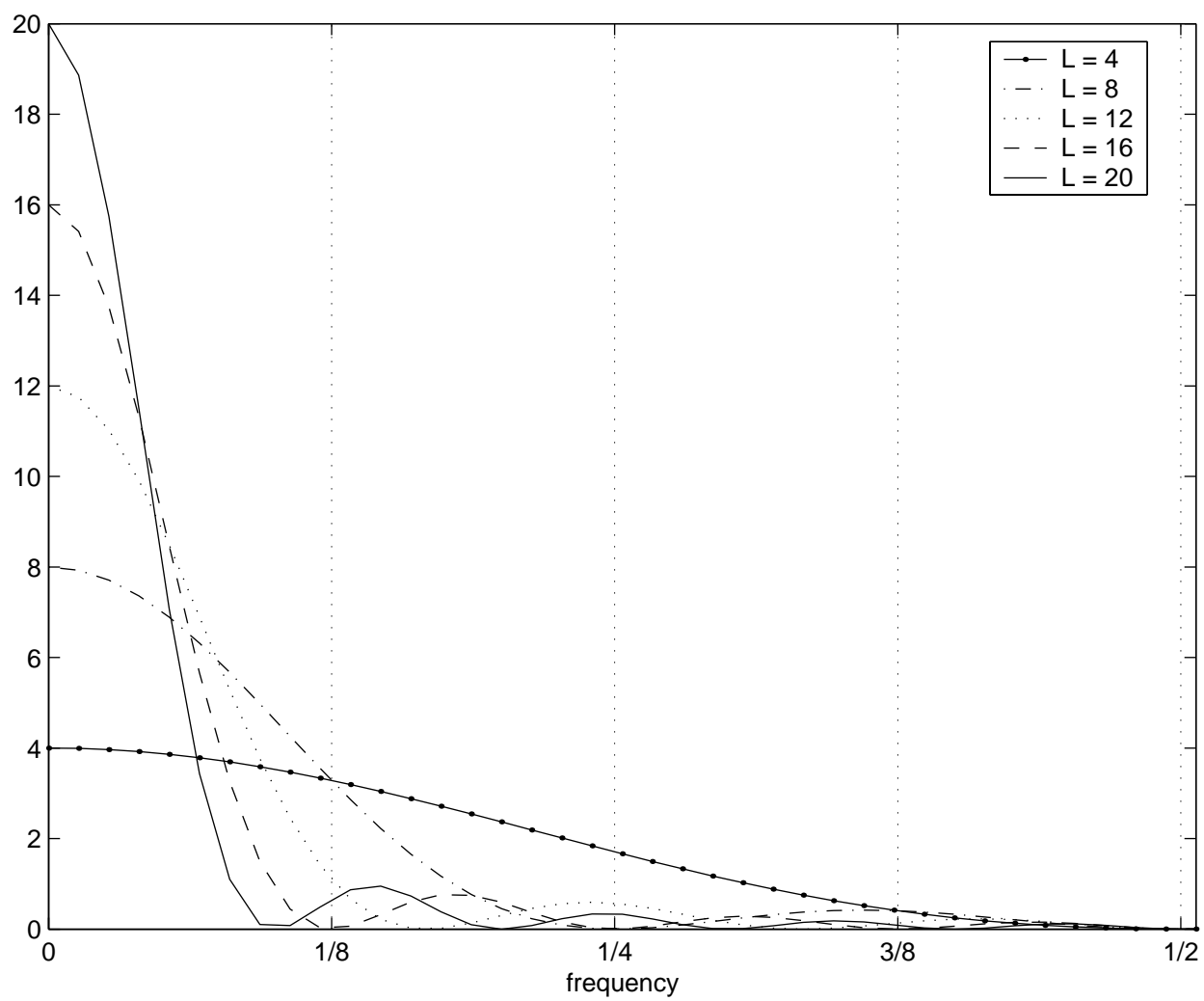


Figure 3: Transfer Functions

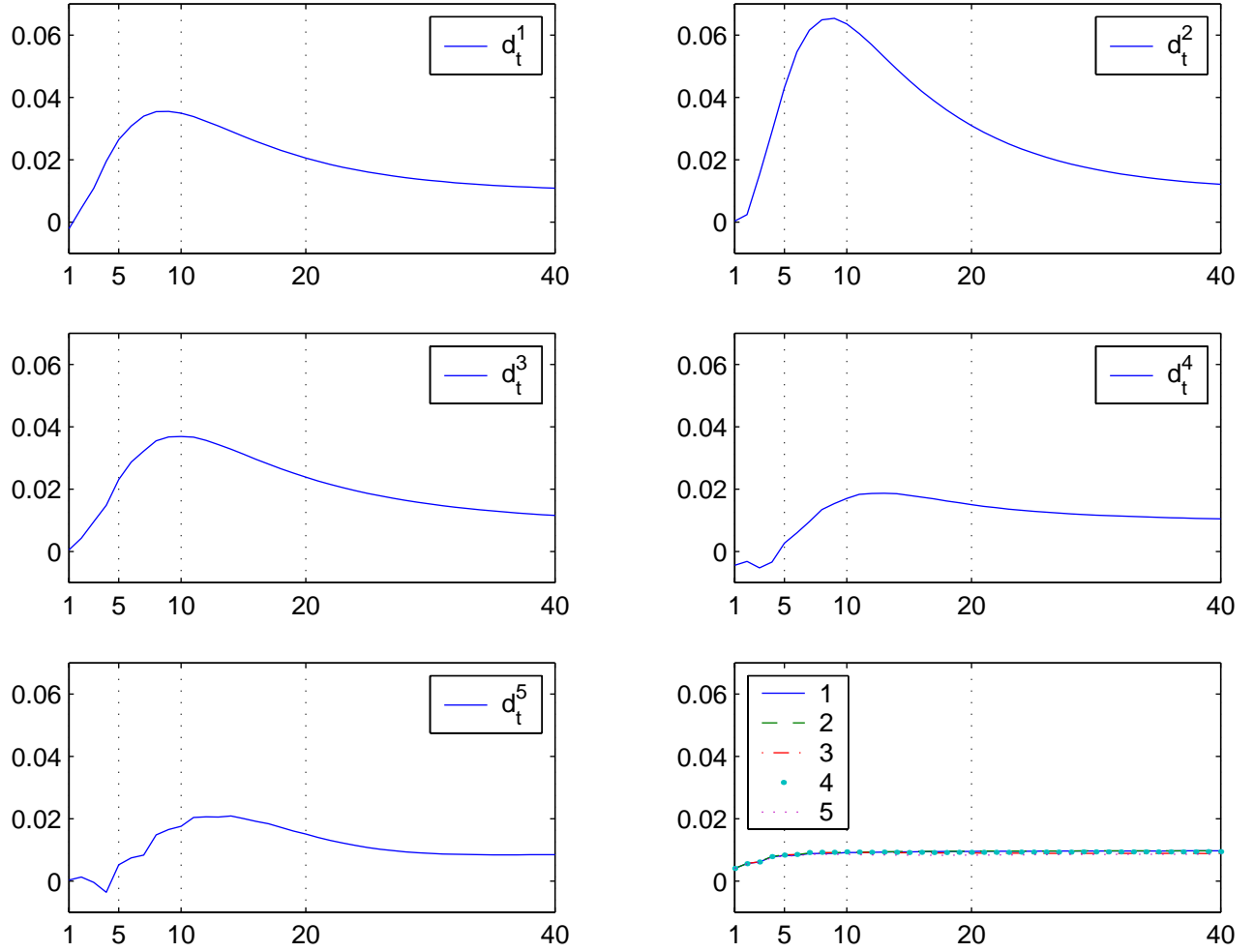


Figure 4: Impulse Response Functions to an Innovation in Aggregate Consumption. This figure reports impulse functions for the dividend processes for each of the five B/M portfolios. The bottom right panel depicts the impulse-response function for consumption. The time units on the horizontal axes are quarters.

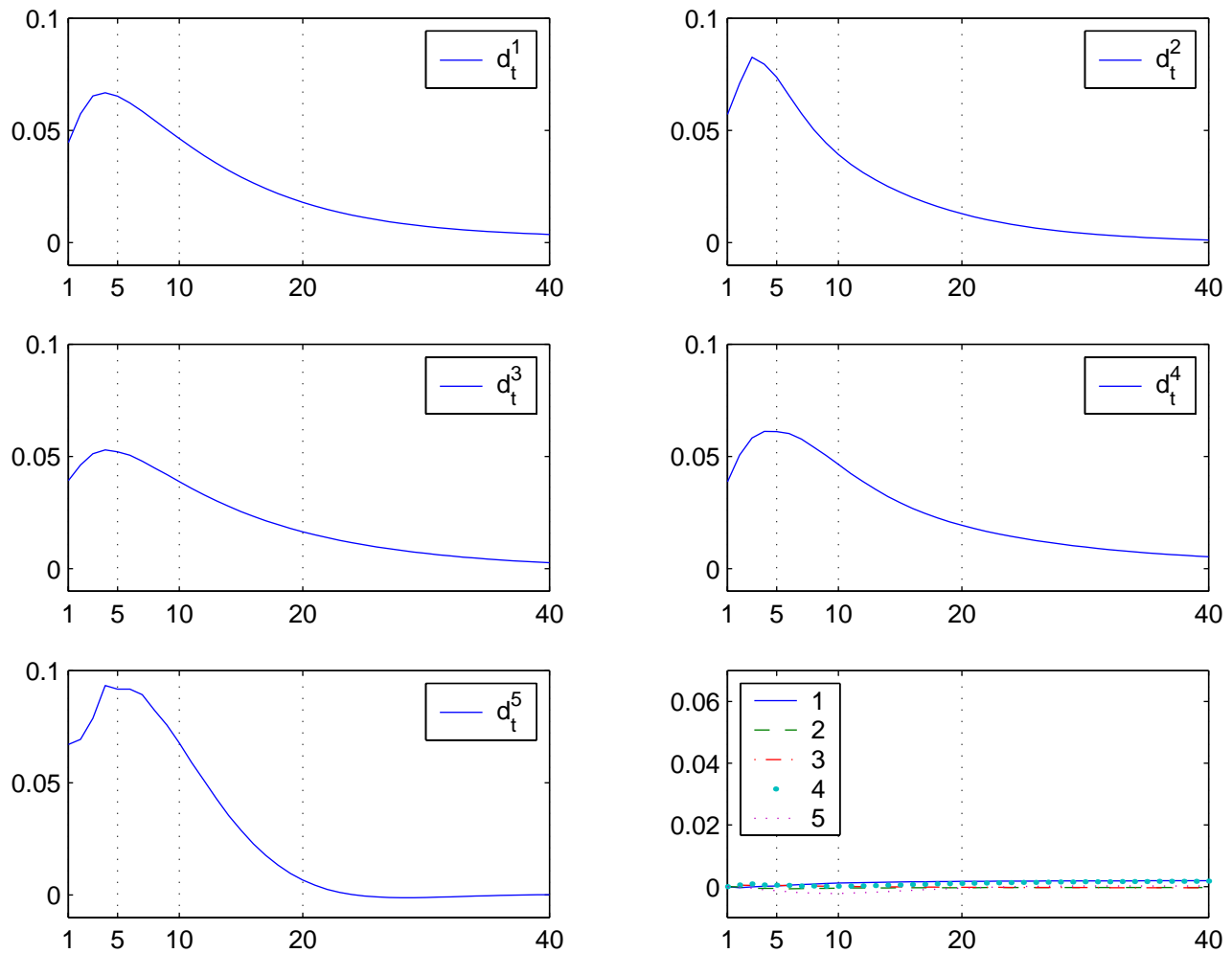


Figure 5: Impulse Response Functions to Dividend Innovations. This figure reports impulse functions for the dividend processes for each of the five B/M portfolios. The bottom right panel depicts the impulse-response function for aggregate consumption. The time units on the horizontal axes are quarters.

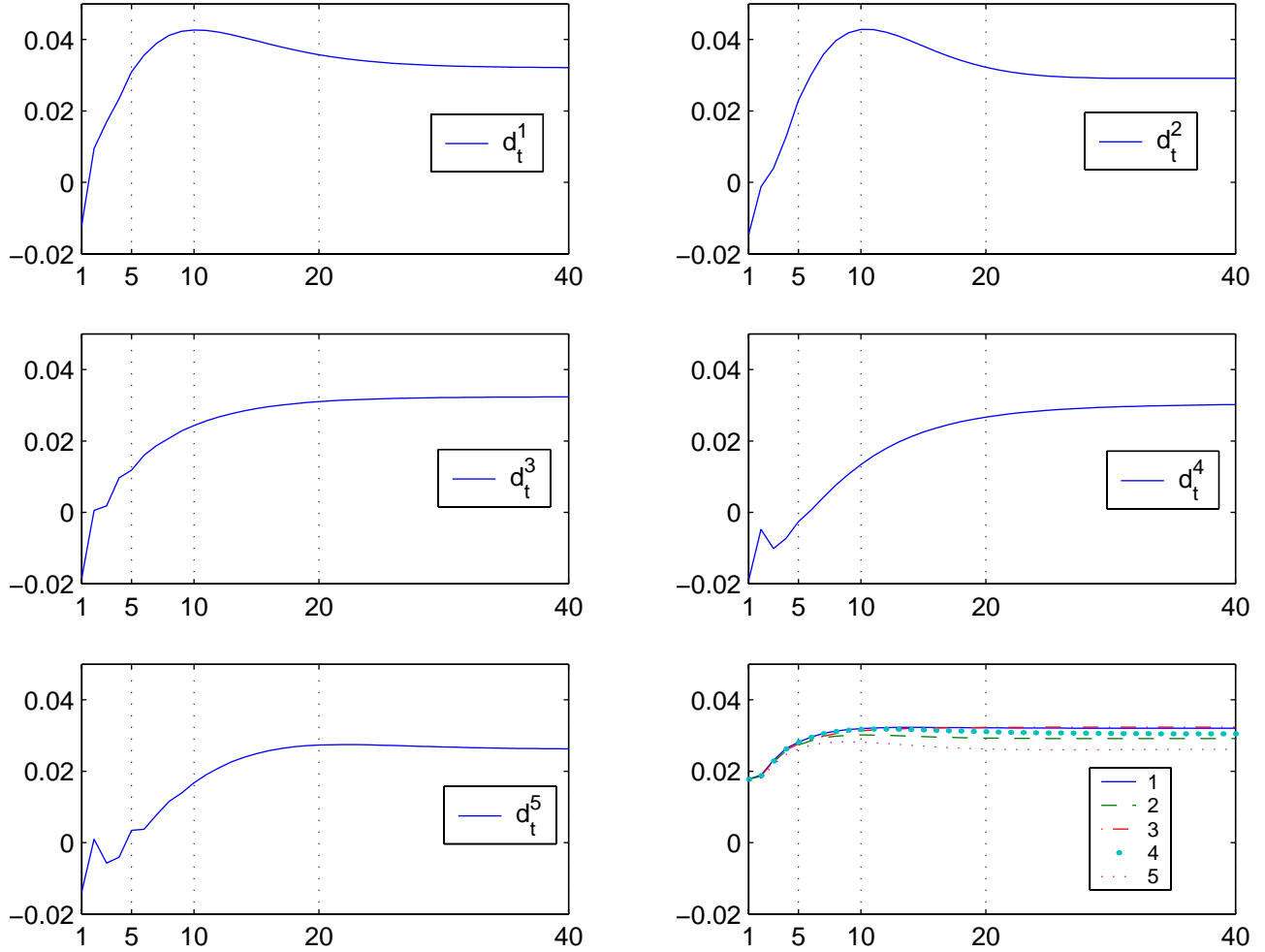


Figure 6: Impulse Response Functions to an Innovation in Proprietors' Consumption. This figure reports impulse functions for the dividend processes for each of the five B/M portfolios. The bottom right panel depicts the impulse-response function for consumption. The time units on the horizontal axes are quarters.

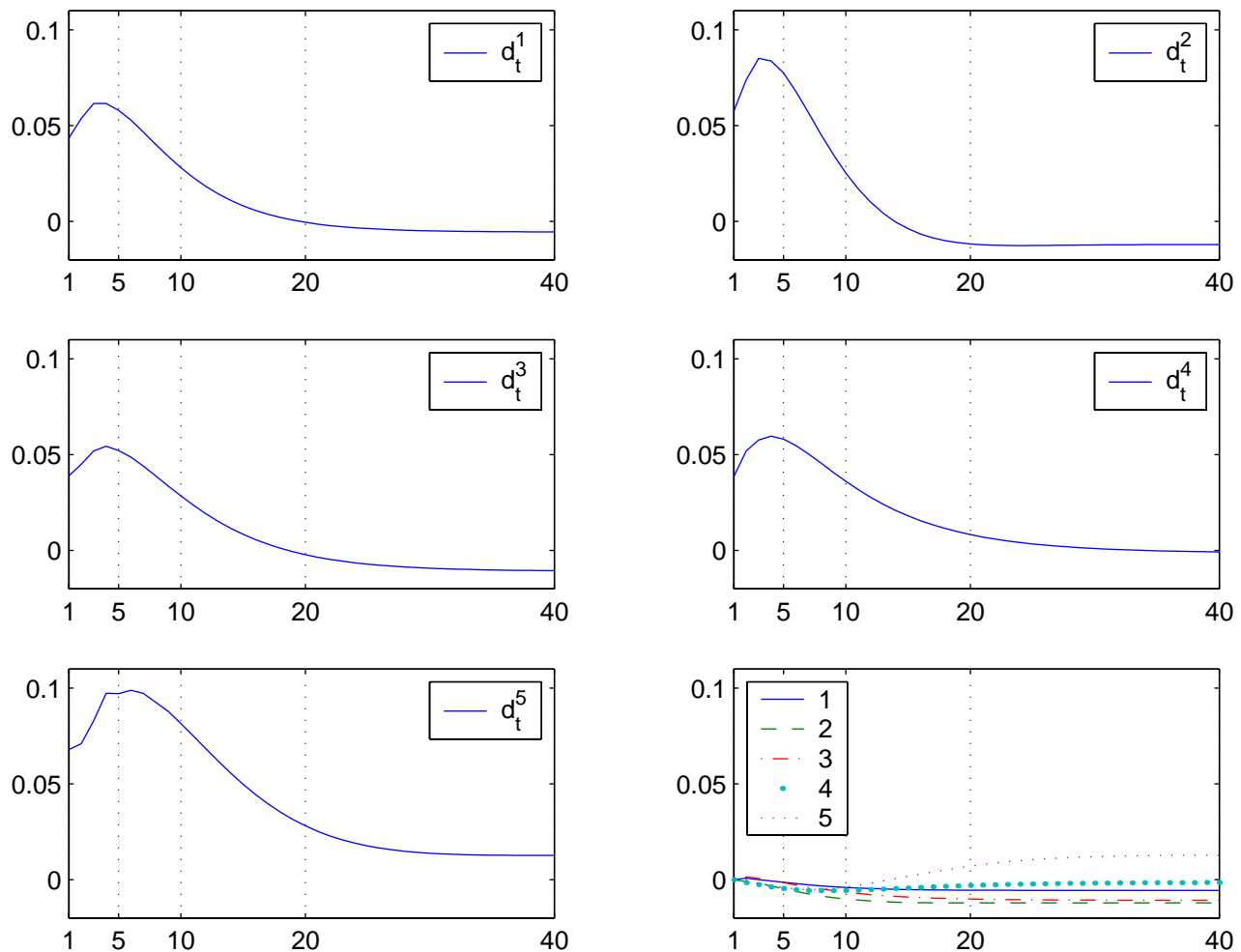


Figure 7: Impulse Response Functions to Dividend Innovations. This figure reports impulse functions for the dividend processes for each of the five B/M portfolios. The bottom right panel depicts the impulse-response function for proprietor's consumption. The time units on the horizontal axes are quarters.

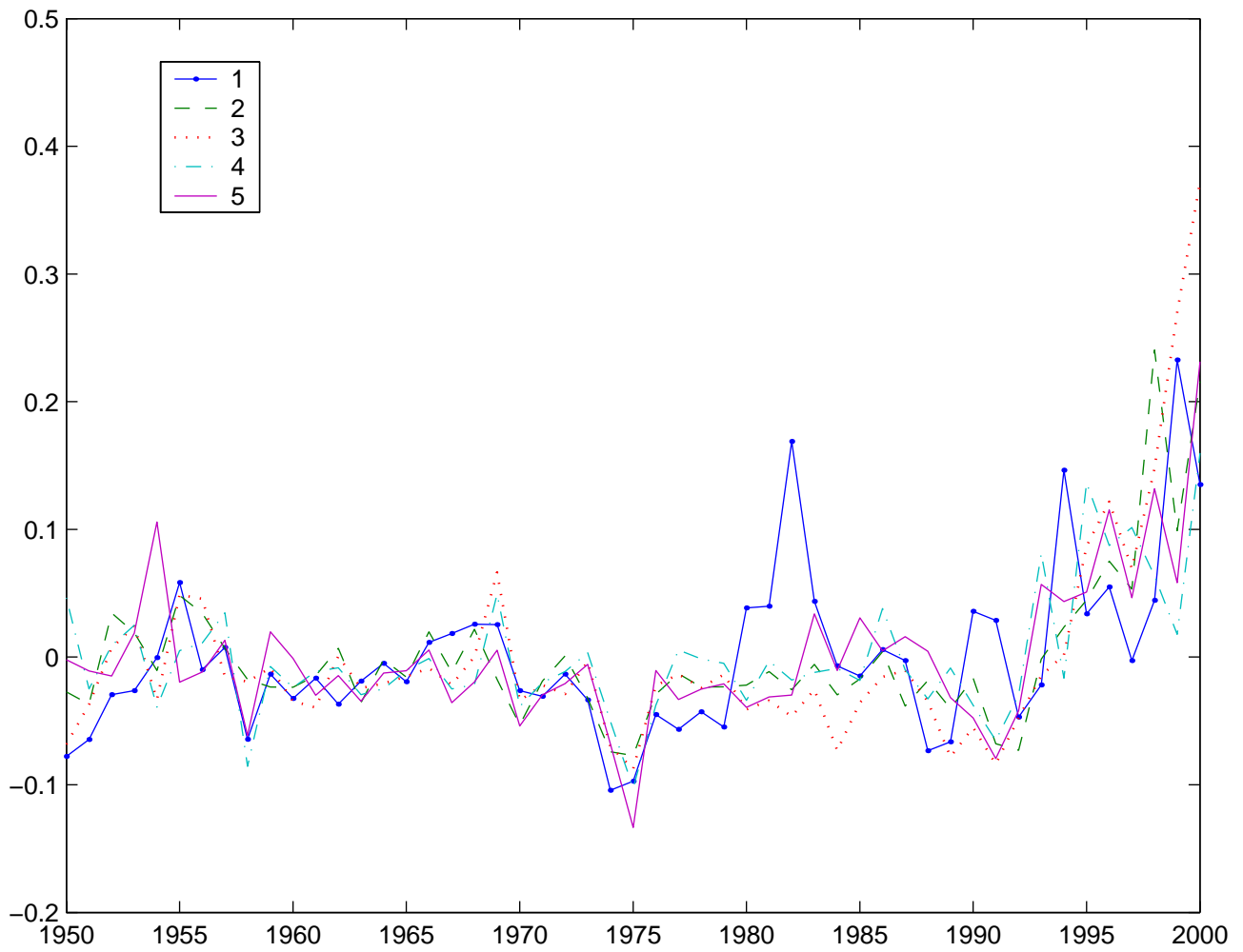


Figure 8: Log of cash flows relative to lagged book value.