GDP Mimicking Portfolios and the Cross-Section of Stock Returns

Abstract

The components of GDP (residential investment, durables, nondurables, equipment and software, and business structures) display a pronounced lead-lag structure. We investigate the implications of this lead-lag structure for the cross-section of asset returns. We find that the leading GDP components perform well in explaining the returns of 25 size and book-to-market portfolios and do reasonably well in explaining the returns of 10 momentum portfolios. The lagging components do a poor job at explaining the returns of 25 size and book-to-market portfolios but explain the return of momentum portfolios very well. A three-factor model with the market risk premium, one leading and one lagging GDP component compares very favorably with the Carhart four-factor model in jointly explaining the returns on 25 size/book-to-market portfolios, 10 momentum portfolios and 30 industry portfolios.

1 Introduction

The Fama and French (1992, 1993) and Carhart (1997) factor models explain the cross-section of asset returns reasonably well. The size, value, and momentum factors used in these models do, however, lack a sound theoretical foundation. A popular alternative, dating back at least to Chen, Roll, and Ross (1986), is to use macroeconomic variables as factors to explain the cross-section of returns. A common approach in this literature is to relate asset returns to changes in GDP or GDP components. GDP in this context can be thought of as a measure of business cycle or recession risk, or as an aggregate which encompasses consumption and investment.

The empirical results are ambiguous. Chen, Roll, and Ross (1986), Campbell (1996) and Griffin, Ji, and Martin (2003) find that aggregate GDP is not informative for stock returns. Vassalou (2003), on the other hand, shows that a mimicking portfolio designed to capture news on future aggregate GDP growth performs about as well as the Fama-French model. Koijen, Lustig, and Nieuwerburgh (2012) argue that the value premium is a compensation for macroeconomic risk. They show that the Cochrane and Piazzesi (2005)-factor, which forecasts future economic activity (namely the Chicago Fed National Activity Index and aggregate GDP), explains the returns of book-to-market sorted portfolios.

Empirical tests based on GDP components also produce mixed results. The components related to consumption have been extensively analyzed in the literature on consumption-based asset pricing models (see Ludvigson (2012) for a recent survey). Yogo (2006) rationalizes the growth of the stock of durables as a factor. Cochrane (1991, 1996), Li, Vassalou, and Xing (2006), and Belo (2010) advocate the use of investment-related GDP components in asset pricing models.

The empirical success of the models is often judged by how well they explain the returns of 25 portfolios sorted on size and book-to-market.[1] Only few papers have analyzed whether

[1]This practice has been criticized recently by Lewellen, Nagel, and Shanken (2010). They suggest (p.

GDP-based models can explain the returns on portfolios sorted by momentum. Again, the results are inconclusive. Chordia and Shivakumar (2002) and Liu and Zhang (2008) conclude that momentum returns are related to macro variables while Griffin, Ji, and Martin (2003) and Cooper, Gutierrez, and Hameed (2004) find no such relation.

Asset prices should only change when new information becomes available. Against this background the growth rate of aggregate GDP may not be the best choice of a state variable. It is well known that there is a pronounced lead-lag structure in the components of GDP (see e.g. Greenwood and Hercowitz (1991), Gomme, Kydland, and Rupert (2001), Davis and Heathcote (2005), Fisher (2007), Leamer (2007)). In particular, residential investment (RES) leads the GDP, followed by durables (DUR) and nondurables (NDU). Business structures (BST) and equipment and software (EQS), on the other hand, lag GDP. Because aggregate GDP is an average over leading and lagging components, it is a noisy measure of GDP-related news.

In this paper, we investigate the implications of the lead-lag structure of GDP components for the cross-section of asset returns. Ours is the first paper to analyze the explanatory power of aggregate GDP and GDP components in a unified framework. We consider the five GDP components listed above.[2] Our test assets comprise the 25 portfolios sorted on size and book-to-market as well as 10 portfolios sorted on momentum and 30 industry portfolios available from Kenneth French's homepage. We follow Breeden, Gibbons, and Litzenberger (1989), Vassalou (2003), Adrian, Etula, and Muir (2011), among others, and construct factor mimicking portfolios for aggregate GDP and the GDP components.

We find that aggregate GDP does not explain the cross-section of returns. The leading GDP components (residential investment and durables) perform very well in explaining the returns of 25 portfolios sorted on size and book-to-market and do reasonably well in

176) "to include other portfolios in the tests, sorted, for example, by industry, beta, or other characteristics." We follow this suggestion.

[2]We do not consider exports and government spending in this paper. These GDP components play no role in the asset pricing literature. They also do not show a pronounced cyclical pattern (Leamer (2007)).

explaining the returns on 10 momentum portfolios. The lagging GDP components, on the other hand, explain the returns of the momentum portfolios very well but fail to explain the returns of the size and book-to-market sorted portfolios. Finally, a three-factor model with the market risk premium, one leading and one lagging GDP component (residential investment and business structures, respectively) compares very favorably with the Carhart four-factor model in jointly explaining the returns on 25 size/book-to-market portfolios, 10 momentum portfolios and 30 industry portfolios.[3]

Our findings have important implications for empirical asset pricing tests using real measures of economic activity as factors. Aggregate GDP is an average of leading and lagging components. However, leading components provide a better explanation of the cross-section of size and book-to-market returns than lagging GDP components or aggregate GDP. Thus, the fact that previous studies did not account for the lead-lag structure may explain why earlier GDP-related asset pricing tests yielded weak results at best. We add further to the literature by showing that lagged GDP components do a good job at explaining the return on momentum portfolios, a result which is in line with Chordia and Shivakumar (2002) and Liu and Zhang (2008). Finally, while some recent papers show that financial variables which predict future aggregate economic activity explain the cross-section of stock returns (e.g. Petkova (2006), Koijen, Lustig, and Nieuwerburgh (2012)), we show that GDP itself also explains the cross-section of returns once the lead-lag pattern of GDP components is taken into account.

The remainder of the paper is structured as follows. In Section 2 we discuss the lead-lag structure of GDP components. Section 3 describes the construction and characteristics of the factor-mimicking portfolios. In Section 4 we describe our data set and the econometric methodology. Section 5 presents the results of our asset pricing tests, Section 6 describes

[3]In a recent paper Adrian, Etula, and Muir (2011) show that a factor which proxies for shocks to the aggregate leverage of security broker-dealers explains the cross-section of risky asset returns well. Our GDP-based factor model competes favorably with their model. Using a similar test design and a similar set of test assets (but a longer time series), we obtain R^2s of the same order of magnitude as theirs'.

the robustness checks we have performed, Section 7 concludes.

2 Stylized Facts: Lead and Lag in GDP Components

The components of GDP do not move in lockstep, but rather with a quite robust lead and lag to aggregate GDP: residential investment leads the business cycle, followed by durable consumption, and nondurable consumption, followed by the lagging components investment in equipment and software, and investment in business structures. This empirical fact has been neglected in the asset pricing literature, but is well documented in the empirical and theoretical macroeconomic literature.

Empirical Observations. We use annual data for aggregate GDP and components of GDP. Annual data on residential investment, durables, nondurables, equipment and software and business structures come from the Bureau of Economic Analysis (BEA) for the period from 1951 to 2010.[4] Nondurables are measured as "nondurable goods" (NIPA 2.3.4/5, Line 8) and "services" (NIPA 2.3.4/5, Line 13) as is common in the literature. We use the corresponding price indices and population reported by the BEA (NIPA 7.1, Line 18) to compute real per capita growth rates.

The lead and lag pattern in GDP components can best be observed by looking at recessions and recoveries. Recessions materialize from one up to two years earlier in residential investment (the vanguard of the business cycle) than for investment in business structures (the rear guard of the business cycle). Similarly, recoveries can usually be observed first in residential investment and last in business structures.

Figure 1 illustrates the behavior of the average annual per capita real growth rate of each GDP component compared to aggregate GDP during the ten recessions (according to

[4]NIPA Tables 5.3.4/5, Lines 17, 3, and 9; and NIPA Tables 2.3.4/5, Lines 3, 8, and 19.

the NBER definition) which occurred between 1951 and 2010. As can be seen, all GDP components closely track the aggregate from the business cycle peak (zero on the horizontal axis) to the trough and recovery. However, the lead of residential investment and the lag of investment in business structures is easily observable in the figure. Leamer (2007) provides an impressive recession-by-recession comparison of the GDP components. He finds that the lead and lag behavior can be observed not only averaged across all recessions but is a relatively robust feature of each individual recession. Descriptive statistics in Table 1 and forecasting regressions of aggregate GDP on lagged GDP components strongly confirm the lead and lag structure.[5] In the forecasting regressions we regress (using yearly data) the change in per-capita real GDP on the lagged value of the change in the GDP components. Residential investments has by far the largest standardized slope coefficient (0.43) and the largest t-value and R^2 (5.06 and 0.20, respectively). Thus, residential investments are a good predictor of future GDP. The standardized slope of EQS and BST, on the other hand, is negative. It is also noteworthy that residential investment is the only GDP component that is positively correlated with the market excess return.

– Insert FIGURE 1 about here –

– Insert TABLE 1 about here –

Literature. As noted above, the lead-lag relation between the GDP components is a well established fact. Several authors have attempted to explain this pattern Greenwood and Hercowitz (1991) were the first to theoretically analyze the cyclical behavior of investment in household capital and business capital. Their aim is to construct a model which explains the procyclical behavior of residential investment, and its lead with respect to business investment. The model can generate procyclicality but fails to produce the lead pattern (Greenwood and Hercowitz (1991, p.1210)). Gomme, Kydland, and Rupert (2001) show

[5]Using the event time approach of Koijen, Lustig, and Nieuwerburgh (2012), we provide further evidence on the lead and lag behavior of GDP components in the Online Appendix to this paper.

that including production time brings the model much closer to the data, generating cyclical co-movements and a lag in business investment. Also Davis and Heathcote (2005) calibrate a model which is able to reproduce the fact that residential and nonresidential investment co-move with GDP and consumption. However, their model does not reproduce the empirical fact that "nonresidential investment lags GDP, whereas residential investment leads GDP" (Davis and Heathcote (2005, p.752)). Fisher (2007) provides another possible explanation for why household investment leads nonresidential business investment over the business cycle. He shows that if the traditional home production model is extended such that household capital is complementary to business capital, the model can generate the observed leads and lags.

3 GDP-Mimicking Portfolios

GDP and its components are not traded assets, and they are only observable at low frequencies. We therefore follow the literature and construct mimicking portfolios, portfolios of traded assets that track a particular factor.[6] In our analysis of GDP components, we construct tracking portfolios by projecting aggregate GDP and each of the five GDP components discussed in Section 2 on the return space of traded assets. We construct six portfolios that have maximum correlation with aggregate GDP and the five GDP components, respectively. These portfolios have the same asset pricing relevant information as the true factors (Balduzzi and Robotti (2008)).[7]

The mimicking portfolio approach has several advantages for our empirical design. First, the returns on stock portfolios can be measured accurately while GDP and its components

[6] See e.g. Breeden, Gibbons, and Litzenberger (1989), Lamont (2001), Vassalou (2003), Cochrane (2005, p. 109, p. 170), Ferson, Siegel, and Xu (2006), Ang, Hodrick, Xing, and Zhang (2006), Jagannathan and Wang (2007), Balduzzi and Robotti (2008), Cooper and Priestley (2011), Adrian, Etula, and Muir (2011), Menkhoff, Sarno, Schmeling, and Schrimpf (2012).

[7] The mimicking portfolios are interesting for portfolio advice as well. They can be interpreted as hedges against the risk of the factor they represent (Cochrane (2005, p.167)).

are observed with error (Breeden, Gibbons, and Litzenberger (1989)).[8] Therefore, statistical inference based on mimicking portfolios will be more accurate. Second, stock market returns are observed at higher frequency than GDP and its components. Therefore, we can use monthly data instead of yearly or quarterly data (Breeden, Gibbons, and Litzenberger (1989), Vassalou (2003)). Using monthly data increases the number of time-series observations in our sample. This, in turn, allows us to expand the set of test assets. We include industry and momentum portfolios together with the standard set of 25 size and book-to-market-sorted portfolios. Third, our tests based on mimicking portfolios yield estimates of the risk premia of the factors. These estimates can be compared to the sample mean of the mimicking portfolio excess returns. We are thus able to judge whether the estimated risk premia are plausible, a major concern of Lewellen, Nagel, and Shanken (2010). Finally, when the factors are portfolios of traded assets we can estimate time-series regressions to complement and validate the results of our cross-sectional tests (Jagannathan and Wang (2007)).

In the main paper we only present results obtained using mimicking portfolios. Appendix 2 provides results of tests based on the real per capita growth rates of aggregate GDP and the five GDP components. The results of these tests are qualitatively similar to those presented in the paper. We therefore conclude that our results are not driven by our mimicking-portfolio-based approach.

Construction. We closely follow Breeden, Gibbons, and Litzenberger (1989), Vassalou (2003) and Adrian, Etula, and Muir (2011) in the construction of our mimicking portfolios. We run the following OLS regression for each of the $j = 1, ..., 6$ annual real per capita growth rates of aggregate GDP and its five components ($\triangle Y_{j,t}$):

$$\triangle Y_{j,t} = a_j + \mathbf{p}_j' \left[\mathbf{FF6}_t,\ WML_t\right] + \epsilon_{j,t}\ \forall j, \tag{1}$$

[8]Importantly, it is likely that the different GDP components are subject to different degrees of measurement error, making comparisons between the variables even more difficult.

where $\mathbf{p}_j$ are 7×1 slope coefficients, $\mathbf{FF6}_t$ are annual real excess returns of the six Fama-French portfolios sorted on size and book-to-market (Fama and French (1993)) and WML_t is the momentum factor "winners minus losers" (Carhart (1997)).[9] The selection of these assets is motivated by the well-known fact that they span the mean-variance frontier of a large set of stock market returns (Fama and French (1996)). We normalize the sum of the seven portfolio weights for aggregate GDP and each GDP component to one, $\hat{\mathbf{w}}_j = \hat{\mathbf{p}}_j / (\mathbf{1}'\hat{\mathbf{p}}_j)$. Once we have the mimicking portfolio weights, we can use them to measure the monthly returns of the mimicking portfolios. The mimicking portfolio return for GDP variable j at time t is given by

$$MPm_{j,t} = \hat{\mathbf{w}}_j' \left[\mathbf{FF6m}_t,\ WMLm_t\right],\ \forall j \tag{2}$$

where $\mathbf{MPm}_t = [MPm_{1,t}, ..., MPm_{6,t}]'$ is a 6×1 vector of mimicking portfolio returns for month t. These returns substitute for the changes in aggregate GDP (GDP), residential investment (RES), durables (DUR), nondurables (NDU), equipment and software (EQS), and business structures (BST).

A Look at the Mimicking Portfolio Factors. The empirical results of the OLS regressions for the construction of the mimicking portfolios are presented in Table 2. The unadjusted R^2 for all OLS regressions are within a range between 10% and 25% and are thus comparable to those in Vassalou (2003) and higher than the ones reported by Lamont (2001). Panel A of the table shows the normalized weights. They already foreshadow some of our main results. The leading GDP components, residential investment and durables, load heavily on the value factor. Consider the mimicking portfolio for residential investments as an example. It has weight 1.63 on small value stocks, weight 0.09 on large value stocks, weight -1.13 on small growth stocks and weight 0.65 on large growth stocks. This

[9] We use stock return data available from the web site of Kenneth R. French (Fama and French (1993)). See Section 4 for details on the data.

results in a total exposure of 2.20 (1.63+0.09-(-1.13)-0.65) to the value factor. The corresponding figure for the mimicking portfolio for durables is 2.00. By contrast, the GDP components lagging the business cycles such as equipment and software and business structures have much lower exposure to value (1.21 and 0.84, respectively). The pattern for the exposure to size is quite similar. Residential investments and durables have the highest size exposure (0.47=-1.13-0.01+1.63-0.65-(-0.72)-0.09) and 0.79=-1.92+0.40+2.00-1.39-(-1.17)-(-0.53), respectively) while business structure has the lowest size exposure (-1.56=0.23-0.25-0.92-(-0.95)-0.53-1.04).

This picture changes completely when we consider the exposure to momentum in the last row of Panel A in Table 2. Here, the mimicking portfolios for residential investment, nondurables, and durables have the lowest weights while the mimicking portfolios for the GDP components lagging the business cycle are highly invested in the momentum portfolio.

We further analyze the mean-variance properties of the mimicking portfolios (similar to Jagannathan and Wang (2007) and Adrian, Etula, and Muir (2011)). The first line of Panel B of Table 2 shows the mean return of the mimicking portfolios. As mentioned above we will use these mean returns as benchmark values for the factor risk premia that we estimate in our asset pricing tests. Lines 2 and 3 of Panel B show the return standard deviation and the Sharpe ratios of the mimicking portfolios. It is noteworthy that the Sharpe ratios decline monotonically as we move from the leading GDP components to the lagging components. Figure 2 plots the efficient frontier based on the six Fama-French portfolios and the momentum portfolio. It further shows the mimicking portfolios for each of the five GDP components and the one for aggregate GDP. The mimicking portfolio for residential investments is reasonably close to the efficient frontier (although the GRS statistic rejects the null of efficiency).

The lower part of Panel B shows the intercept and slope coefficients of time series regressions in which we regress the returns of the GDP-mimicking portfolios on the four factors of the Carhart model. The coefficients are mainly statistically significant and match with the findings from Panel A of Table 2. The exposure to the size and value factor declines as we move from the leading to the lagging GDP components while the reverse is true for the momentum factor. It is also interesting to note that the market beta is positive for the leading GDP components and negative for the lagging components.

– Insert TABLE 2 about here –

– Insert FIGURE 2 about here –

4 Model, Estimation, and Data

Model. Recessions are bad news for investors (Chen, Roll, and Ross (1986), Campbell (2000), Cochrane (2005), p.172). The prospect of an upcoming recession gives reason to expect a lower level of production and consumption, lower dividends and higher distress risk for equity investments. Investors with jobs are subject to larger idiosyncratic labor income and unemployment risk than in normal times. The stochastic discount factor can be expected to be highest at the onset of a recession. Investors will avoid assets which perform poorly in recessions, and such assets should therefore compensate investors with higher expected returns.

We use the stochastic discount factor (SDF) representation to estimate linear factor models. More precisely, we consider the empirical SDF specification

$$m_t = 1 - \widetilde{\mathbf{f}}_t' \mathbf{b}, \tag{3}$$

where m_t denotes the SDF, $\widetilde{\mathbf{f}}_t$ are K de-meaned factors, $\widetilde{\mathbf{f}}_t = (\mathbf{f}_t - \boldsymbol{\mu})$, and $\mathbf{b}$ are K factor loadings. We use an ICAPM specifications and therefore include the market excess return, MKT_t, as a factor (Fama (1996)). In most specifications, we augment the SDF with *one* of the j GDP component mimicking portfolios. It is included as a factor capturing recession risk.

The linear SDF specification in Equation (3) implies that N excess returns, $\mathbf{R}_t$, are related to the factors by (Burnside (2011)):

$$E(\mathbf{R}_t) = cov(\mathbf{R}_t,\ \mathbf{f}_t)\,\mathbf{b}. \tag{4}$$

A given estimate of $\mathbf{b}$ allows to make an inference on whether a specific factor helps to price the considered set of assets given the other factors (Cochrane (2005)). Equation 4 also underscores an economic restriction on the sign of the estimated SDF loadings $\mathbf{b}$. Theory suggests that an economically sensible SDF should take on high values in "bad times" (recessions) and low values in "good times". Assets which covary counter-cyclically with the SDF should provide higher expected returns (Campbell (2000), Cochrane (2005)). All five components of GDP are pro-cyclical (see Section 2). Therefore, the estimates of the SDF loading for a specific GDP component (and its mimicking portfolio) should be positive.[10]

The SDF representation is transferable to the traditional expected return-beta representation. Rearranging Equation (4) gives:

$$E(\mathbf{R}_t) = \boldsymbol{\beta}\boldsymbol{\lambda}, \tag{5}$$

where $\boldsymbol{\beta} = cov(\mathbf{R}_t, \mathbf{f}_t)\,\boldsymbol{\Sigma}_{ff}^{-1}$ is a $N \times K$ matrix of factor betas, $\boldsymbol{\lambda} = \boldsymbol{\Sigma}_{ff}\mathbf{b}$ is a $K \times 1$ vector of factor risk premia, and $\boldsymbol{\Sigma}_{ff}$ is the covariance matrix of factors. The factor risk premium can be interpreted as the price the SDF assigns to the factor. If the factor is a traded asset (e.g., a GDP mimicking portfolio), the estimated factor risk premium should be equal to its sample mean (and the factor should thus price itself). We exploit this relation in order to check wether the estimated factor risk premia are economically plausible (Lewellen, Nagel, and Shanken (2010)).

[10]Recently, Maio and Santa-Clara (2012) have shown that many popular multifactor models do not meet this criterion. Estimated SDF loadings frequently have the wrong sign and are thus inconsistent with the ICAPM.

Estimation. Our estimation methodology follows Cochrane (2005) and Burnside (2010, 2011). We report Generalized Method of Moments (GMM) estimates for SDF loadings $\mathbf{b}$ and implied factor risk premia $\boldsymbol{\lambda}$. In principle, if the model is specified correctly, several normalizations of the SDF are equivalent. However, Burnside (2010) shows that the SDF specification with de-meaned factors has greater power to reject misspecified models than other normalizations. We include a common pricing error (or constant) in all models. This constant should be zero for each model. Testing the estimated constant against zero allows us to check the validity of the model. We re-estimated all models without including a constant. The results are shown in the appendix. Standard errors are adjusted for heteroscedasticity and serial correlation.

We estimate linear factor models using the $N + K + \kappa$ empirical moment restrictions

$$\mathbf{g} = g_T\left[\gamma,\ \mathbf{b},\ \boldsymbol{\mu},\ vec\left(\boldsymbol{\Sigma}_{ff}\right)\right] = E_T \begin{bmatrix} \mathbf{R}_t\left[1 - \left(\mathbf{f}_t - \boldsymbol{\mu}\right)'\mathbf{b}\right] - \gamma \\ \mathbf{f}_t - \boldsymbol{\mu} \\ vec\left[\left(\mathbf{f}_t - \boldsymbol{\mu}\right)\left(\mathbf{f}_t - \boldsymbol{\mu}\right)'\right] - vec\left(\boldsymbol{\Sigma}_{ff}\right) \end{bmatrix}, \tag{6}$$

where γ is a common pricing error (a constant) and $vec\left(\boldsymbol{\Sigma}_{ff}\right)$ denotes the $\kappa = K\left(K+1\right)/2$ unique elements of the covariance matrix of factors. We use first-stage GMM with the standard identity matrix as a weighting matrix and require the GMM estimator to set $\hat{\boldsymbol{\mu}}$ and $\hat{\boldsymbol{\Sigma}}_{ff}$ equal to their sample counterparts. Burnside (2011) shows that using the moment conditions in Equation (6) along with the identity weighting matrix results in numerical equivalence between the SDF-based GMM estimates and the two-pass Fama-MacBeth estimates of γ and $\boldsymbol{\lambda}$. This fact makes our estimates easy to interpret and comparable to the vast literature that uses the Fama and MacBeth (1973) two-stage estimation procedure.

Standard errors of the parameters are based on the HAC-robust covariance estimator of $\mathbf{S} = \sum_{j=-\infty}^{\infty} E\left[\mathbf{g}\mathbf{g}'\right]$ proposed by Newey and West (1987) using the automatic lag length selection procedure of Andrews (1991). As described in Cochrane (2005) and Burnside (2010, 2011), adding the additional $K + \kappa$ moment conditions on the factor means and factor covariance matrix facilitates the correction of the standard errors of $\hat{\gamma}$, $\hat{\mathbf{b}}$ and $\hat{\boldsymbol{\lambda}}$ for the fact that $\boldsymbol{\mu}$ and $\boldsymbol{\Sigma}_{ff}$ are estimated. As measures of model fit we report the cross-sectional OLS R^2, the mean absolute error (MAE), and the Hansen-Jagannathan distance (HJ) with simulation-based p-values (Hansen and Jagannathan (1997), Kan and Robotti (2008)). We also report the cross-sectional GLS R^2. It measures how close the best combination of the factors is to the mean-variance frontier of tested assets and serves to illustrate the economic validity of the cross-sectional fit (Kandel and Stambaugh (1995), Lewellen, Nagel, and Shanken (2010)).

Return Data. For the asset pricing tests, we use the 25 Fama-French portfolios sorted by size and book-to-market, 10 momentum portfolios, 30 industry portfolios, the market premium MKT, SMB, HML, WML (the momentum factor), and the one-period T-bill rate available on the web site of Kenneth R. French (Fama and French (1993)). The momentum returns use the "2-12" convention, i.e. they are based on the returns from the previous 12 month excluding the last one. We use annual data from 1951 to 2010, and monthly data from January 1951 to December 2010; stock market returns are in excess of the one-period T-bill rate. We deflate yearly returns by the price index implied by our consumption measure (nondurables). To deflate monthly returns, we use the monthly CPI available from the Bureau of Labor Statistics.

5 Asset Pricing Tests

5.1 GDP Components and the Cross-Section of Stock Returns

Size and Value. We use monthly GDP component mimicking portfolios throughout this section. Table 3 shows our test results when we use 25 size and book-to-market-sorted portfolios as test assets. We see from specification (1) that the market factor is unable to explain the returns of the size and book-to-market portfolios. The constant (the common pricing error) is large (1.34%) and significant; the SDF loading b as well as the factor risk premium λ are negative and insignificant.[11] Adding aggregate GDP as a factor does not improve the model (specification (2)) .

Next, we substitute aggregate GDP with *one* of the GDP components. The ordering of the components in the table follows the lead-lag pattern. The leading components are reported first and the lagging components last. In specification (3), we include residential investment, which is the vanguard of the business cycle. The constant is relatively small, 0.30%, and insignificant. The SDF loading on residential investment and the corresponding factor risk premium are positive and significant at conventional levels. The OLS (GLS) R^2 is about 0.76 (0.46), and the HJ-distance is smaller than in specification (1) and (2). However, there is also some evidence of misspecification. The estimated factor risk premium for residential investment is only 1.11%, as compared to the sample mean of the factor of 1.41%, and the factor risk premium for the market excess return is too small as well. In specification (4), we find a similar model fit for durables. The constant is statistically and economically insignificant (0.05%) and the SDF loading is positive and significant. The model explains 72% of the cross-sectional variation in size and book-to-market sorted portfolio returns (with a GLS R^2 of 0.43). The next row, specification (5), shows results for nondurables. The SDF loading and the factor price are still positive and significant. However, all measures of model fit indicate a less favorable model fit, e.g. the OLS (GLS) R^2 is only 0.26 (0.16).

In line (6), the table reports results for equipment and software. We find a large and significant constant of 1.65%. The SDF loading is (insignificantly) negative, the estimate of the factor risk premium is also (insignificantly) negative and the measures of model fit are similar to those for nondurables. Since all GDP components are pro-cyclical, the SDF loading should be positive. We conclude that the estimate in specification (6) has the wrong

[11] All factors are traded assets. Thus, we can interpret the pricing error economically as an annualized return of 12×1.34%=16.08% not explained by the factors. Note that the estimated intercept and the factor risk premia are numerically equivalent to the traditional Fama-MacBeth estimates (Burnside (2011)).

sign. This is confirmed when comparing the estimate of the factor risk premium to the mean of the factor return: The estimated risk premium is -0.82% and is more than two standard errors away from the sample mean of +1.11% (see Table 2). In specification (7), we find very similar results for business structures. Even though the measures of model fit suggest a good fit (OLS (GLS) R^2 of 0.68 (0.31)), the model is clearly misspecified since the constant is large (2.39%) and the slope coefficient is negative and thus economically implausible.

In summary, we find that the leading GDP components are able to explain the returns of 25 size and book-to-market-sorted portfolios reasonably well. The coefficients have the expected signs, are significant, and explain up to 76% of the cross-sectional variation of the returns on the test assets. The lagging GDP components, on the other hand, yield negative estimates of the factor risk premium. Appendix 1 shows the estimates of restricted models in which we force the constant to be zero. We find that our results are robust to this alternative specification. In Appendix 2 we report results based on actual (annual) GDP data rather than on mimicking portfolios. They are qualitatively similar.

– Insert TABLE 3 about here –

Momentum. Table 4 shows our test results when we use 10 momentum-sorted portfolios as test assets. The structure of the table is similar to Table 3. Specification (1) shows the traditional CAPM, specification (2) a model with aggregate GDP, and specifications (3) to (7) show the performance of the GDP components as risk factors, beginning with the vanguard GDP component (residential investment) and closing with the rear guard of the business cycle (business structures).

The leading GDP components continue to perform well. They produce small pricing errors (i.e., a small and insignificant constant), positive and significant factor risk premia, and reasonably high R^2s. Once we consider the lagging GDP components, however, we find that our previous results are turned upside down. We find that the lagging GDP components capture the average returns of the momentum portfolios quite well, and better than the leading GDP components. Focusing on the rear guard of the business cycle, business structures in specification (7), the constant is small (0.36%), the SDF loading is *positive* and significant at conventional levels. This stands in stark contrast to the result based on size and book-to-market-sorted portfolios where we found *negative* estimates of the SDF loading and factor risk premia. However, there are also indications of misspecification. In particular, the estimated factor risk premium (1.06%), albeit having the right sign, is too large compared to the sample mean of the factor return (0.55%).

Appendix 1 presents results of restricted models in which we force the constant to be zero. Again, we find that our results are robust to this alternative specification. Appendix 2 shows results based on actual (annual) GDP data rather than on mimicking portfolios. They are qualitatively similar. However, the leading GDP components underperform the lagging components more clearly.

– Insert TABLE 4 about here –

5.2 A GDP-Based Three-Factor Model

From our previous analysis we know that leading GDP components can explain the average returns of size and book-to-market portfolios very well and those of momentum portfolios reasonably well. The lagging GDP components, on the other hand, explain the average returns of momentum portfolios very well. Thus, a three factor model which includes the market excess return, residential investment as the most leading GDP component, and business structures as the most lagging GDP component is a natural choice when it comes to jointly explaining the returns on size, value, and momentum portfolios. This specification should captures the lead and lag structure of the GDP components. The two GDP components are chosen to share the job of pricing a large cross-section of assets: The task of residential investments is to price the size and book-to-market-sorted portfolios while the task of business structures is to price the momentum portfolios.

Size, Value, and Momentum. Table 5 shows the results that we obtain when we simultaneously use 25 double sorted size/book-to-market portfolios and 10 single sorted momentum portfolios as test assets. In specifications (1) and (2) we find that the traditional CAPM and the CAPM augmented by aggregate GDP as a state variable are not able to explain the returns of the test assets. Scrolling through the two-factor specifications (3) to (7), the table shows that leading GDP components perform better in pricing the 35 portfolios than the lagging GDP components.

Results for our GDP-based three-factor model are reported in line (8). The estimated constant is very close to zero (0.01%) and insignificant (t-statistic of 0.03). The estimated factor risk premium for residential investment is 1.44% (t: 4.40), which is indistinguishable from the sample mean of 1.41%. Similarly, the estimated risk premium for business structures, 0.54% (t: 1.81), is significant and very close to its sample mean of 0.55%. Even the estimated market risk premium, 0.59%, is indistinguishable from its sample mean of 0.56% (t: 1.24). Thus, all four point estimates, the constant and the three factor risk premia, are economically sensible. The OLS (GLS) R^2 is 0.82 (0.42), suggesting a good model fit. The good fit is confirmed by a low MAE of 0.09. Only the HJ-distance statistic has not improved much as compared to the other specifications, although it does not reject the three-factor model at the 1% level.

Figure 3 provides a graphical illustration of the 35 individual pricing errors. The CAPM fails to price the 35 test assets. Adding business structures (the same holds for aggregate GDP) does not help to reduce the pricing errors of the 25 size/book-to-market portfolios. Adding the vanguard GDP component, residential investment, instead results in a much better fit. The size/book-to-market portfolios move towards the diagonal line. Including both residential investment and business structure results in even lower pricing errors. Most importantly, the extreme momentum portfolios (MomH and MomL) move closer to the 45° line.

Again, Appendix 1 shows the results that we obtain when we impose a zero constant.

They are qualitatively similar to the results presented in the text. Appendix 2 shows results based on actual (annual) GDP data rather than on mimicking portfolios. The three factor model performs well. We estimate significantly positive factor risk premia for the market excess return and residential investments. The R^2 is 0.63. The risk premium for business structures is positive but insignificant.

– Insert TABLE 5 about here –

– Insert FIGURE 3 about here –

Time-Series Regressions. It is a well-established fact that small stocks have larger average returns than big stocks, and high book-to-market (value) stocks have larger average returns than low book-to-market (growth) stocks. Similarly, portfolios of past winners (high momentum) have larger average returns than portfolios of past losers (low momentum). We have documented in the previous section that our GDP-based three-factor model prices the size/book-to-market and momentum portfolios well. Thus, our three factors must be capturing the size, value and momentum premium. To shed more light on this issue we estimate time-series regressions in which we regress the returns of the 35 size/book-to-market and momentum-sorted portfolios on the market excess return and the returns of the factor-mimicking portfolios for residential investment and business structures. The results are reported in Table 6.

The upper Panel shows the betas of the 25 size and book-to-market-sorted portfolios as well as their t-statistics. The market excess return does not generate a spread in betas that is in line with the stylized facts reported above. Small firm betas are not generally larger than large firm betas, and high book-to-market firms do not have higher betas than low book-to-market firms (they rather have lower betas, which is at odds with the value premium in observed stock returns). We thus conclude that the market excess return does not explain the size and value effect. This picture changes significantly when we consider the betas with respect to residential investment. With one exception (the lowest book-to-market quintile) the betas decrease monotonically as we move from small to large firms. Similarly, within each size quintile the betas increase almost monotonically as we move from low book-to-market portfolios to high book-to-market portfolios. We thus conclude that the residential investment-factor explains the size and the value premia. The third factor, business structures, does not explain the size and value premium. In fact, betas for large firms are larger than those for small firms, which is at odds with the size effect. There is no clear pattern with respect to the book-to-market sort.

The lower Panel of Table 6 shows the betas of the 10 momentum portfolios as well as their t-statistics. The betas with respect to the market excess returns across the ten momentum portfolios are u-shaped. Thus, the market excess return does not explain the momentum effect. The betas with respect to residential investment are slightly more in line with the momentum effect. They tend to increase as we move from the loser portfolios to the winner portfolios. However, the spread in betas is small; the difference between the betas for the two extreme portfolios is only 0.24. The third factor, business structures, captures the momentum effect almost perfectly. The betas increase monotonically as we move from the loser portfolios to the winner portfolios, and the spread between the extreme portfolios is large (0.85).

– Insert TABLE 6 about here –

Table 7 shows the alphas of the time-series regressions described above as well as the (unadjusted) R^2s. Of the 25 size- and book-to-market-sorted portfolios only three have a significant alpha. The three significant alphas range from 0.18% to 0.20% which corresponds to an annualized return of about 2.4%. We thus conclude that the pricing errors implied by our three-factor model are reasonably small. The R^2s tend to be larger for big stocks than for small stocks. Fifteen of the R^2s are larger than 0.80, and none is less than 0.60.

With respect to the momentum portfolios, only the winner portfolio (high momentum) has a significant (at the 5% level) alpha of 0.22%. All other alphas are insignificant and economically small (within the range of -0.20% to 0.17%). All ten R^2s are above 0.80. Notwithstanding the good performance of the GDP-based three-factor model in the individual time-series regressions, the Gibbons, Ross, and Shanken (1989) test statistic calculated across all 35 alphas rejects the model at the 1% level.

In summary, the results of the time-series regressions imply that the vanguard of the business cycle, residential investment, produces betas which are in line with the average returns of the size / book-to-market portfolios. The rear guard of the business cycle, business structures, on the other hand, produces betas which are in line with the returns on momentum-sorted portfolios. Only four of the 35 portfolios have individually significant alphas, and these alphas are small in economic terms.

– Insert TABLE 7 about here –

Industry Portfolios and Horse Races. As suggested by Lewellen, Nagel, and Shanken (2010), we further expand the set of test assets and include 30 industry portfolios together with 25 double sorted size/book-to-market portfolios and 10 momentum portfolios.[12] Within this demanding framework we test our three-factor model against the Carhart four-factor model. Panel A of Table 8 shows the results of four models, the CAPM, the Carhart four-factor model, a GDP-based two-factor model (market excess return and residential investment) and our GDP-based three-factor model including the market excess return, residential investment and business structures. The CAPM fails. The pricing error (the constant) is large and significant, and the estimate of the risk premium is negative. The Carhart model performs better. The risk premia for the book-to-market factor and the momentum factor are significant. However, the constant, albeit smaller than in the CAPM, is still significant.

[12]We use the same set of test assets as Adrian, Etula, and Muir (2011) (but our time-series is longer). Adrian, Etula, and Muir show that "shocks to the aggregate leverage of security broker-dealers" can explain the returns of the 65 test assets well. They find R^2s ranging from 0.45 (single factor) to 0.55 (adding the three Fama-French factors and the momentum factor).

Specification (3), the GDP-based two-factor model, shows that the market factor combined with residential investment explains the cross-section of the 65 portfolios already well. The constant is smaller than in the Carhart model (but still significant at the 10% level) and the risk premium for residential investment is positive and significant. Specification (4), our three-factor model, performs even better. The constant is 0.30% and insignificant (t-statistic 1.17). In contrast, the constant of the Fama-French/Carhart four-factor model (specification (2)) is twice as large and significantly different from zero (t-statistic 2.79). Residential investment as well as business structures have both significant risk premia (at the 1% and 5% level, respectively). However, the estimates of the factor risk premia are not as close to their sample means as those reported in Table 5 above. The OLS R^2 is 0.54, slightly smaller than the R^2 of the Carhart model (0.56). The GLS $R^2$is 0.26 and is slightly larger than the one in the Carhart model (0.24).

Figure 4 provides a graphical illustration of the pricing error implied by the GDP-based two-factor and three-factor model. It is clearly visible that the three-factor model (model (4) in the table performs better than the three-factor model that includes only residential investments. The better fit is driven by the momentum portfolios (MomL, MomH) which are much closer to the 45° line..

Finally, we test whether SMB, HML, and WML contain pricing relevant information beyond that contained in our GDP-based three-factor model. We orthogonalize the Carhart factors (SMB, HML, WML) with respect to the GDP mimicking portfolios RES and BST and include the orthogonalized factors in an extended model.[13] We find that SDF loadings as well as risk premia for SMB and HML are not significant once we account for the GDP-based factors. The factor price for WML is substantially reduced in economic terms, from 0.72% in specification (4) to 0.19%, but is still significant (t: 2.05). The results for RES and BST are mainly unchanged. Therefore, it seems fair to conclude that the GDP-based three

[13]We follow Ferguson and Shockley (2003) to extract the orthogonal portion of the SMB, HML, and WML factors. For example, we regress HML on RES and BST, and collect the time-series residuals plus the estimated intercept.

factor model captures most of the pricing relevant information inherent in the traditional four-factor model.

– Insert TABLE 8 about here –

– Insert FIGURE 4 about here –

6 Robustness (Online Appendix)

We have performed a large number of robustness test. In order to economize on space we do not report the results in this paper but rather present them in an online appendix. This section briefly describes the additional test we have performed and their main results. Table numbers refer to the tables in the online appendix.

In the main text we use as test assets 25 size and book-to-market sorted portfolios, 10 momentum portfolios, the combination of these two sets, and and the extended set plus 30 industry portfolios. We perform similar tests for 25 portfolios sorted on size and momentum. The results (shown in table OA.2) are very similar to those presented in Table 5 of the paper.

In the paper we showed the results of our GDP-based three-factor model only for the extended set of 35 test assets and the full set which also includes the industry portfolios. We have also estimated three-factor model on the 25 size and book-to-market sorted portfolios and the 10 momentum portfolios. The results (shown in table OA.3) are similar to those presented in the paper.

Vassalou (2003) constructs a mimicking portfolios that tracks future GDP. She then shows that this factor prices 25 portfolios sorted on size and book-to-market about as well as the Fama/French three-factor model. Constructing a mimicking portfolio which predicts future changes (rather than contemporaneous changes) in GDP or its components is an obvious way to eliminate the lag in some of the GDP components and aggregate GDP. We therefore adopt the approach of Vassalou (2003). In line with our expectations we find that the performance of the lagging GDP components improves significantly (see table OA.4).

In particular the estimated factor risk premia are positive. These findings corroborate our conclusion that the lead-lag structure in aggregate GDP and its components has important asset pricing implications.

When we split our samples in two parts (1951-1980 and 1981-2010) we obtain results that are comparable to those for the full sample shown in the text (see tables OA.5 and OA.6).

We construct our mimicking portfolio over the entire data set and then test the ability of the mimicking portfolios to price the test assets. One potential objection against this procedure is that the data used to construct the mimicking portfolios was unavailable during the sample period. We therefore also perform out-of-sample tests. We use the data from 1951-1980 to construct the mimicking portfolios and then test whether these mimicking portfolios price our test assets in 1981. We then proceed using an expanding windows approach, i.e. we next use the data from 1951-1981 to construct mimicking portfolios and then test their cross-sectional pricing ability for the return of the test assets in 1982, and so on. The results (shown in table OA.7) of the out-of-sample tests are very similar to those that we obtain when we apply the in-sample procedure to the same sample period (i.e. 1981-2010; these results are shown in table OA.6).

The mimicking portfolios for the six GDP components are constructed independently. For each component we identify the weights of the portfolio that has maximum correlation with the growth rate of the respective GDP component. Alternatively we first estimate a first-order VAR system of the five GDP components. We then construct mimicking portfolios that have maximum correlation with the VAR innovations. When we use this alternative set of factor-mimicking portfolios we obtain results which are similar to those presented in the text (see table OA.8).

In the paper we use annual GDP data to construct the mimicking portfolios. We repeated the analysis using quarterly data instead (tables OA.9 and OA.10). The results for durable consumption are a bit odd (the mimicking portfolio has extreme weights and the results of the asset pricing tests differ significantly from those obtained using annual data). The results for the other four components are similar to those presented in the paper and yield the same conclusions.

7 Conclusion

Relating stock market returns to GDP has been the topic of many previous studies in financial economics. Empirical results have been mixed at best. We add to this literature by taking the lead-lag structure of GDP components into account. We find that the lead-lag structure of GDP components is mirrored in the factor structure of size, book-to-market, and momentum portfolio returns. The leading GDP components - residential investment in particular - explain the returns on size and book-to-market portfolios very well. The lagging GDP components (business structures in particular), on the other hand, capture momentum returns surprisingly well but completely fail to explain the returns on size and book-to-market sorted portfolios.

Based on these results, we propose and test a GDP-based three-factor model with the market excess return, one leading GDP component, and one lagging GDP component. This model accounts for the lead-lag structure of GDP. We find that our GDP-based three-factor model is able to explain the cross-section of returns for 65 stock portfolios sorted on size, book-to-market, momentum, and industry at least as well as the Fama-French/Carhart four-factor model.

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Appendix

1 Estimation without Intercept

The inclusion or exclusion of a constant (common pricing error) can have a substantial impact on cross-sectional regression results (see e.g. Burnside (2011)). However, Table A.1 shows that we can draw the same conclusions from estimation without an intercept.

– Insert TABLE A.1 about here –

2 Growth Rates of Components

Table A.2 documents that our findings are robust to the use of growth rates of aggregate GDP and GDP components instead of the mimicking portfolios. We also present estimates without intercept in Table A.3.

– Insert TABLE A.2 about here –

– Insert TABLE A.3 about here –

Table 1: Descriptive Statistics

Panel A reports descriptive statistics for U.S. real per capita growth rates for aggregate GDP and components of GDP. MKT is the stock market excess return, as in the Fama/French data library. Panel B provides forecasting regressions of GDP components with respect to future aggregate GDP (all variables are real per capita growth rates). Newey-West corrected t-statistics are reported in parentheses (automatic lag length selection). All data are annual and the sample period is from 1951 to 2010.

Panel A: Leads and lags of real annual per capita growth rates

Aggregate GDP or GDP Component	Mean	SD	Correlation with $\triangle GDP_t$ $t-2$	$\triangle GDP_t$ $t-1$	$\triangle GDP_t$ t	MKT_t t
$\triangle$Aggregate GDP (GDP)	2.00	2.29	-0.04	0.10	1.00	-0.13
$\triangle$Residential Investment (RES)	0.57	12.81	0.10	0.44	0.56	0.14
$\triangle$Durables (DUR)	3.71	6.48	0.09	0.20	0.73	-0.04
$\triangle$Nondurables (NDU)	1.93	1.27	-0.11	0.30	0.81	-0.01
$\triangle$Equip. & Software (EQS)	4.46	7.82	-0.03	-0.03	0.82	-0.22
$\triangle$Business Structures (BST)	0.80	7.53	-0.22	-0.24	0.46	-0.20

Correlation between GDP components	RES	DUR	NDU	EQS
DUR	0.73			
NDU	0.59	0.7		
EQS	0.41	0.71	0.65	
BST	-0.06	0.17	0.43	0.56

Panel B: Forecasting regressions for standardized real per capita growth rates:

$$(\triangle GDP_t - \mu_{GDP})/\sigma_{GDP} = \alpha + \beta\ (\triangle Y_{j,t-1} - \mu_{Yj})/\sigma_{Yj} + \epsilon_t$$

	β	$t(\beta)$	R^2
GDP	0.10	(0.72)	0.01
RES	0.43	(4.67)	0.20
DUR	0.20	(1.41)	0.04
NDU	0.30	(2.28)	0.09
EQS	-0.03	(-0.22)	0.00
BST	-0.24	(-1.89)	0.06

Table 2: GDP Component Mimicking Portfolios

Panel A reports estimates of $j = 1, ..., 6$ mimicking portfolio weights for aggregate GDP (GDP), residential investment (RES), durables (DUR), nondurables (NDU), equipment and software (EQS) and business structures (BST). We regress the real per capita growth rate of annual aggregate GDP and each of the annual GDP components ($\triangle Y_{j,t}$) on six annual Fama-French portfolios, $\mathbf{FF6}_t$, sorted by size and book-to-market (low/small, mid/small, high/small, low/big, mid/big, high/big) and the momentum factor, WML_t:

$$\triangle Y_{j,t} = a_j + \mathbf{p}'_j \left[\mathbf{FF6}_t,\ WML_t\right] + \epsilon_{j,t}.$$

The resulting weights $\hat{\mathbf{p}}_j$ are normalized, such that their sum is one: $\hat{\mathbf{w}}_j = \hat{\mathbf{p}}_j \left(\mathbf{1}'\hat{\mathbf{p}}_{,j}\right)^{-1}$. Monthly GDP mimicking portfolios are calculated as: $MPm_{j,t} = \hat{\mathbf{w}}'_j \left[\mathbf{FF6m}_t,\ WMLm_t\right]$, where $\mathbf{FF6m}_t$, and $WMLm_t$ are monthly measured returns of the six Fama-French portfolios and the momentum factor. Panel B reports the mean (%), standard deviation (%), Sharpe ratio and the factor exposures (betas) of the six monthly GDP mimicking portfolios:

$$MPm_{j,t} = \alpha_j + \beta_{MKT,j} MKT_t + \beta_{SMB,j} SMB_t + \beta_{HML,j} HML_t + \beta_{WML,j} WML_t,$$

where MKT is the market excess return, SMB is the small minus big factor, HML is the high minus low factor, and WML is the winner minus loser (momentum) factor. T-statistics are reported in parentheses and are based on the Newey and West (1987) HAC covariance matrix with automatic lag length selection according to Andrews (1991). The sample period is from January 1951 to December 2010.

	GDP	RES	DUR	NDU	EQS	BST
Panel A:	Normalized GDP mimicking portfolio weights					
low/small	-0.79	-1.13	-1.92	-0.48	-0.75	0.23
mid/small	-0.30	-0.01	0.40	0.01	-1.37	-0.25
high/small	0.83	1.63	2.00	0.31	1.97	-0.92
low/big	0.04	0.65	1.39	-0.24	0.57	-0.95
mid/big	0.52	-0.72	-1.17	0.04	0.27	0.53
high/big	-0.39	0.09	-0.53	0.56	-0.94	1.04
momentum	1.09	0.49	0.84	0.80	1.25	1.33
Panel B:	Statistics of monthly mimicking portfolio factors					
Mean (%)	1.03	1.41	1.65	0.99	1.11	0.55
SD (%)	5.17	4.00	5.47	3.61	6.22	6.27
Sharpe ratio	0.20	0.35	0.30	0.28	0.18	0.09
α (%)	0.16	0.32	0.62	0.01	0.25	-0.31
	(3.16)	(3.92)	(4.41)	(1.26)	(2.48)	(-4.42)
β_{MKT}	-0.17	0.46	0.02	0.20	-0.30	-0.25
	(-11.29)	(19.20)	(0.42)	(112.09)	(-10.76)	(-12.37)
β_{SMB}	-0.41	0.23	0.02	-0.18	-0.31	-0.69
	(-18.89)	(5.67)	(0.29)	(-54.85)	(-7.12)	(-20.13)
β_{HML}	0.54	1.09	0.88	0.85	0.30	0.43
	(22.42)	(28.39)	(13.24)	(193.59)	(5.85)	(13.25)
β_{WML}	1.12	0.53	0.92	0.80	1.30	1.29
	(70.04)	(19.08)	(18.66)	(270.82)	(39.37)	(55.16)

Table 3: GDP Mimicking Portfolio Factors: 25 Fama-French Portfolios

The table reports GMM estimates of asset pricing models given by

$$E(\mathbf{R}_t) = \gamma + \boldsymbol{\beta}\boldsymbol{\lambda}.$$

Estimates of the SDF loadings $\mathbf{b}$ and a constant γ are obtained by exploiting the moment restrictions $E(\mathbf{R}_t[1-(\mathbf{f}_t-\boldsymbol{\mu})'\mathbf{b}]-\gamma)=0$ and $E(\mathbf{f}_t-\boldsymbol{\mu})=0$, where $\mathbf{R}_t$ is a vector of stock returns and $\mathbf{f}_t$ is a vector of risk factors. The loadings on the stochastic discount factor are multiplied by 100 in the table. Factor risk prices are calculated as $\boldsymbol{\lambda}=\boldsymbol{\Sigma}_{ff}\mathbf{b}$, standard errors are obtained by the delta method, and are corrected for the fact that the covariance matrix of risk factors $\boldsymbol{\Sigma}_{ff}$ is estimated. The stock returns are 25 value-weighted Fama-French portfolios sorted by size and book-to-market. The risk factors are the excess return on the market portfolio (MKT), and factor mimicking portfolios for aggregate GDP (GDP), residential investment (RES), durables (DUR), nondurables (NDU), equipment and software (EQS), and business structures (BST). Estimation is by first-stage GMM using the identity matrix. T-statistics are reported in parentheses and are based on the Newey and West (1987) HAC covariance matrix with automatic lag length selection according to Andrews (1991). We report the cross-sectional OLS R^2, below the cross-sectional GLS R^2, the mean absolute error (MAE), and the Hansen-Jagannathan distance (HJ) with the simulation-based p-value for a test of a zero HJ. All data are monthly and the sample period is from January 1951 to December 2010.

	Const	SDF Loadings ($\mathbf{b}$)		Factor Prices ($\boldsymbol{\lambda}$)		$R^{2\,OLS}_{GLS}$	MAE	HJ(pv)
(1)	γ	MKT		MKT				
	1.34	-2.91		-0.55		0.13	0.15	0.28
	(3.41)	(-1.28)		(-1.27)		0.10		(0.00)
(2)	γ	MKT	GDP	MKT	GDP			
	2.47	-12.61	-7.31	-1.76	-0.89	0.26	0.13	0.28
	(3.47)	(-2.28)	(-1.59)	(-2.50)	(-1.05)	0.14		(0.00)
(3)	γ	MKT	RES	MKT	RES			
	0.30	-0.24	7.06	0.32	1.11	0.76	0.07	0.22
	(0.67)	(-0.09)	(3.76)	(0.63)	(3.10)	0.46		(0.07)
(4)	γ	MKT	DUR	MKT	DUR			
	0.05	5.49	8.56	0.68	2.33	0.72	0.08	0.23
	(0.10)	(1.53)	(4.29)	(1.19)	(4.52)	0.43		(0.04)
(5)	γ	MKT	NDU	MKT	NDU			
	0.12	3.68	7.54	0.61	0.94	0.26	0.14	0.28
	(0.29)	(1.25)	(2.24)	(1.24)	(2.26)	0.16		(0.00)
(6)	γ	MKT	EQS	MKT	EQS			
	1.65	-7.15	-4.02	-0.93	-0.82	0.20	0.14	0.27
	(3.29)	(-1.98)	(-1.52)	(-1.81)	(-1.00)	0.19		(0.00)
(7)	γ	MKT	BST	MKT	BST			
	2.39	-13.49	-7.27	-1.74	-1.38	0.68	0.09	0.25
	(4.13)	(-3.34)	(-2.84)	(-3.34)	(-1.82)	0.31		(0.04)

Table 4: GDP Mimicking Portfolio Factors: 10 Momentum Portfolios

The table reports GMM estimates of asset pricing models given by

$$E(\mathbf{R}_t) = \gamma + \boldsymbol{\beta}\boldsymbol{\lambda}.$$

Estimates of the SDF loadings $\mathbf{b}$ and a constant γ are obtained by exploiting the moment restrictions $E(\mathbf{R}_t[1-(\mathbf{f}_t-\boldsymbol{\mu})'\mathbf{b}]-\gamma) = 0$ and $E(\mathbf{f}_t-\boldsymbol{\mu}) = 0$, where $\mathbf{R}_t$ is a vector of stock returns and $\mathbf{f}_t$ is a vector of risk factors. The loadings on the stochastic discount factor are multiplied by 100 in the table. Factor risk prices are calculated as $\boldsymbol{\lambda} = \boldsymbol{\Sigma}_{ff}\mathbf{b}$, standard errors are obtained by the delta method, and are corrected for the fact that the covariance matrix of risk factors $\boldsymbol{\Sigma}_{ff}$ is estimated. The stock returns are 10 value-weighted momentum portfolios (2-12). The risk factors are the excess return on the market portfolio (MKT), and factor mimicking portfolios for aggregate GDP (GDP), residential investment (RES), durables (DUR), nondurables (NDU), equipment and software (EQS), and business structures (BST). Estimation is by first-stage GMM using the identity matrix. T-statistics are reported in parentheses and are based on the Newey and West (1987) HAC covariance matrix with automatic lag length selection according to Andrews (1991). We report the cross-sectional OLS R^2, below the cross-sectional GLS R^2, the mean absolute error (MAE), and the Hansen-Jagannathan distance (HJ) with the simulation-based p-value for a test of a zero HJ. All data are monthly and the sample period is from January 1951 to December 2010.

	Const	SDF Loadings ($\mathbf{b}$)		Factor Prices ($\boldsymbol{\lambda}$)		$R^{2\,OLS}_{GLS}$	MAE	HJ(pv)
(1)	γ	MKT		MKT				
	1.52	-4.96		-0.93		0.18	0.23	0.23
	(4.27)	(-2.20)		(-2.20)		0.01		(0.00)
(2)	γ	MKT	GDP	MKT	GDP			
	0.25	4.04	4.43	0.39	0.84	0.89	0.10	0.18
	(0.74)	(1.70)	(3.17)	(0.99)	(3.50)	0.39		(0.01)
(3)	γ	MKT	RES	MKT	RES			
	-0.06	-0.05	12.33	0.62	1.96	0.86	0.11	0.20
	(-0.14)	(-0.02)	(2.89)	(1.49)	(3.25)	0.27		(0.00)
(4)	γ	MKT	DUR	MKT	DUR			
	0.17	3.70	5.87	0.46	1.60	0.89	0.10	0.19
	(0.46)	(1.59)	(3.11)	(1.15)	(3.71)	0.37		(0.01)
(5)	γ	MKT	NDU	MKT	NDU			
	0.16	2.77	6.74	0.45	0.85	0.88	0.10	0.19
	(0.49)	(1.29)	(3.17)	(1.18)	(4.16)	0.35		(0.00)
(6)	γ	MKT	EQS	MKT	EQS			
	0.43	3.13	3.62	0.22	1.08	0.90	0.10	0.18
	(1.31)	(1.38)	(3.13)	(0.57)	(3.54)	0.41		(0.01)
(7)	γ	MKT	BST	MKT	BST			
	0.36	3.69	3.72	0.29	1.06	0.89	0.10	0.18
	(1.11)	(1.61)	(3.14)	(1.61)	(3.31)	0.40		(0.01)

Table 5: GDP Mimicking Factors: 25 Fama-French and 10 Momentum Portfolios

The table reports GMM estimates of asset pricing models given by

$$E(\mathbf{R}_t) = \gamma + \boldsymbol{\beta}\boldsymbol{\lambda}.$$

Estimates of the SDF loadings $\mathbf{b}$ and a constant γ are obtained by exploiting the moment restrictions $E(\mathbf{R}_t[1 - (\mathbf{f}_t - \boldsymbol{\mu})'\mathbf{b}] - \gamma) = 0$ and $E(\mathbf{f}_t - \boldsymbol{\mu}) = 0$, where $\mathbf{R}_t$ is a vector of stock returns and $\mathbf{f}_t$ is a vector of risk factors. The loadings on the stochastic discount factor are multiplied by 100 in the table. Factor risk prices are calculated as $\boldsymbol{\lambda} = \boldsymbol{\Sigma}_{ff}\mathbf{b}$, standard errors are obtained by the delta method, and are corrected for the fact that the covariance matrix of risk factors $\boldsymbol{\Sigma}_{ff}$ is estimated. The stock returns are 25 Fama-French portfolios sorted by size and book-to-market and 10 momentum portfolios (2-12). Estimation is by first-stage GMM using the identity matrix. T-statistics are reported in parentheses and are based on the Newey and West (1987) HAC covariance matrix with automatic lag length selection according to Andrews (1991). We report the cross-sectional OLS R^2, below the cross-sectional GLS R^2, the mean absolute error (MAE), and the Hansen-Jagannathan distance (HJ) with the simulation-based p-value for a test of a zero HJ. All data are monthly and the sample period is from January 1951 to December 2010.

	Const	SDF Loadings ($\mathbf{b}$)			Factor Prices ($\boldsymbol{\lambda}$)			$R^{2\,OLS}_{GLS}$	MAE	HJ(pv)
(1)	γ	MKT			MKT					
	1.35	-3.32			-0.62			0.11	0.20	0.36
	(4.23)	(-1.67)			(-1.65)			0.04		(0.00)
(2)	γ	MKT	GDP		MKT	GDP				
	0.57	2.85	3.96		0.20	0.82		0.41	0.18	0.33
	(1.43)	(1.06)	(2.80)		(0.47)	(3.80)		0.24		(0.00)
(3)	γ	MKT	RES		MKT	RES				
	0.16	-0.18	8.80		0.42	1.39		0.79	0.09	0.29
	(0.38)	(-0.07)	(4.79)		(0.88)	(4.25)		0.42		(0.02)
(4)	γ	MKT	DUR		MKT	DUR				
	0.16	4.41	6.86		0.55	1.87		0.78	0.10	0.29
	(0.35)	(1.50)	(3.97)		(1.12)	(5.37)		0.41		(0.02)
(5)	γ	MKT	NDU		MKT	NDU				
	0.08	3.73	7.43		0.62	0.93		0.60	0.14	0.33
	(0.19)	(1.47)	(3.68)		(1.39)	(5.19)		0.25		(0.00)
(6)	γ	MKT	EQS		MKT	EQS				
	0.87	1.29	3.19		-0.08	1.10		0.42	0.18	0.32
	(2.40)	(0.52)	(2.67)		(-0.20)	(3.86)		0.27		(0.00)
(7)	γ	MKT	BST		MKT	BST				
	0.92	0.47	2.17		-0.15	0.80		0.25	0.20	0.36
	(2.59)	(0.20)	(2.10)		(-0.37)	(2.88)		0.08		(0.00)
(8)	γ	MKT	RES	BST	MKT	RES	BST			
	0.01	1.50	8.32	1.06	0.59	1.44	0.54	0.82	0.09	0.29
	(0.03)	(0.56)	(4.45)	(0.97)	(1.24)	(4.40)	(1.81)	0.42		(0.01)

Table 6: Factor Betas

The table shows time-series betas ($\boldsymbol{\beta}_j$) by the regression

$$R_{j,t} = a_j + \beta_{j,MKT} MKT_t + \beta_{j,RES} RES_t + \beta_{j,BST} BST_t + \epsilon_{j,t},$$

where $R_{j,t}$ are 25 Fama-French portfolios and 10 momentum portfolios (2-12). The risk factors are the market excess return (MKT), and factor mimicking portfolios for residential investment (RES) and business structures (BST). T-statistics are based on the Newey and West (1987) HAC covariance matrix with automatic lag length selection according to Andrews (1991). All data are monthly and the sample period is from January 1951 to December 2010.

25 Fama-French portfolios										
	Book-to-Market Equity					Book-to-Market Equity				
	Low	2	3	4	High	Low	2	3	4	High
	β_{MKT}					$t\,(\beta_{MKT})$				
Small	1.26	1.04	0.85	0.75	0.73	19.07	18.41	19.23	19.71	18.55
2	1.32	1.01	0.85	0.79	0.81	29.98	27.37	26.69	0.79	23.03
3	1.27	0.99	0.86	0.80	0.77	37.02	37.17	28.88	29.06	22.96
4	1.22	1.02	0.93	0.85	0.88	41.97	34.34	28.89	29.04	24.92
Big	1.01	0.97	0.93	0.84	0.85	47.44	41.42	30.05	24.33	19.34
	β_{RES}					$t\,(\beta_{RES})$				
Small	-0.07	0.13	0.27	0.38	0.54	-1.13	2.17	5.99	9.42	13.03
2	-0.19	0.09	0.24	0.37	0.53	-4.04	2.31	7.40	12.33	14.08
3	-0.17	0.08	0.20	0.32	0.48	-4.25	3.02	6.99	10.43	15.82
4	-0.17	0.04	0.15	0.25	0.36	-5.57	1.16	4.55	8.59	9.43
Big	-0.04	-0.02	-0.04	0.15	0.26	-2.01	-0.68	-1.40	4.12	6.00
	β_{BST}					$t\,(\beta_{BST})$				
Small	-0.24	-0.22	-0.24	-0.24	-0.32	-4.98	-5.65	-7.81	-9.84	-12.45
2	-0.13	-0.18	-0.18	-0.19	-0.26	-4.04	-6.40	-8.20	-9.65	-11.65
3	-0.11	-0.11	-0.12	-0.12	-0.21	-4.27	-5.43	-5.28	-5.00	-9.65
4	-0.03	-0.05	-0.07	-0.07	-0.12	-1.39	-2.55	-2.77	-3.34	-3.90
Big	-0.00	0.05	0.08	0.04	0.01	-0.25	3.31	3.72	1.74	0.31

10 momentum portfolios										
	1	2	3	4	5	1	2	3	4	5
	6	7	8	9	10	6	7	8	9	10
	β_{MKT}					$t\,(\beta_{MKT})$				
Low	1.12	0.96	0.83	0.85	0.85	27.70	33.69	29.42	29.95	31.89
High	0.92	0.91	0.99	1.07	1.32	33.86	31.95	43.79	42.46	35.11
	β_{RES}					$t\,(\beta_{RES})$				
Low	-0.18	-0.10	-0.03	0.00	0.04	-4.21	-3.70	-0.88	0.12	1.43
High	0.05	0.11	0.11	0.12	0.06	1.88	4.37	5.20	4.95	1.78
	β_{BST}					$t\,(\beta_{BST})$				
Low	-0.57	-0.40	-0.30	-0.17	-0.09	-16.82	-20.51	-9.46	-9.08	-3.92
High	-0.02	0.04	0.14	0.19	0.28	-0.82	2.38	9.24	10.92	14.08

Table 7: Factor Alphas

The table shows time-series alphas (a_j) by the regression

$$R_{j,t} = a_j + \beta_{j,MKT} MKT_t + \beta_{j,RES} RES_t + \beta_{j,BST} BST_t + \epsilon_{j,t}.$$

where $R_{j,t}$ are 25 Fama-French portfolios and 10 momentum portfolios (2-12). The risk factors are the market excess return (MKT), and factor mimicking portfolios for residential investment (RES) and business structures (BST). T-statistics are based on the Newey and West (1987) HAC covariance matrix with automatic lag length selection according to Andrews (1991). The time-series R^2 is unadjusted. GRS is the test statistic suggested by Gibbons, Ross, and Shanken (1989):

$$\frac{T-N-K}{N}[1+\hat{\boldsymbol{\mu}}'\hat{\boldsymbol{\Sigma}}_{ff}^{-1}\hat{\boldsymbol{\mu}}]^{-1}\hat{\boldsymbol{\alpha}}'\hat{\boldsymbol{\Sigma}}_{\epsilon\epsilon}^{-1}\hat{\boldsymbol{\alpha}} \sim F_{N,T-N-K}.$$

All data are monthly and the sample period is from January 1951 to December 2010.

25 Fama-French portfolios										
	Book-to-Market Equity					Book-to-Market Equity				
	Low	2	3	4	High	Low	2	3	4	High
	a_j					$t(a_j)$				
Small	-0.18	0.16	0.09	0.18	0.13	-0.91	0.96	0.75	1.56	1.09
2	0.06	0.14	0.20	0.08	-0.02	0.42	1.36	2.17	0.88	-0.17
3	0.14	0.18	0.10	0.07	0.02	1.31	2.14	1.23	0.83	0.22
4	0.18	0.04	0.10	0.06	-0.09	1.99	0.60	1.25	0.70	-0.91
Big	0.00	0.02	0.11	-0.11	-0.18	0.04	0.25	1.36	-1.14	-1.69
	R^2									
Small	0.63	0.66	0.71	0.74	0.78					
2	0.76	0.78	0.80	0.82	0.82					
3	0.81	0.84	0.83	0.82	0.81					
4	0.87	0.87	0.84	0.82	0.77					
Big	0.88	0.88	0.80	0.75	0.67					
10 momentum portfolios										
	1	2	3	4	5	1	2	3	4	5
	6	7	8	9	10	6	7	8	9	10
	a_j					$t(a_j)$				
Low	-0.20	0.12	0.17	0.09	-0.01	-1.66	1.23	1.83	1.17	-0.13
High	-0.01	-0.08	-0.02	-0.05	0.22	-0.17	-1.23	-0.28	-0.69	2.15
	R^2									
Low	0.86	0.89	0.85	0.85	0.85					
High	0.86	0.86	0.90	0.90	0.80					
	GRS-test: 2.21					p-value: 0.0001				

Table 8: GDP Mimicking Portfolio Factors and 65 Equity Portfolios

The table reports GMM estimates of asset pricing models given by

$$E(\mathbf{R}_t) = \gamma + \boldsymbol{\beta}\boldsymbol{\lambda}.$$

Estimates of the SDF loadings $\mathbf{b}$ and a constant γ are obtained by exploiting the moment restrictions $E(\mathbf{R}_t[1 - (\mathbf{f}_t - \boldsymbol{\mu})'\mathbf{b}] - \gamma) = 0$ and $E(\mathbf{f}_t - \boldsymbol{\mu}) = 0$, where $\mathbf{R}_t$ is a vector of stock returns and $\mathbf{f}_t$ is a vector of risk factors. The loadings on the stochastic discount factor are multiplied by 100 in the table. Factor risk prices are calculated as $\boldsymbol{\lambda} = \boldsymbol{\Sigma}_{ff}\mathbf{b}$, standard errors are obtained by the delta method, and are corrected for the fact that the covariance matrix of risk factors $\boldsymbol{\Sigma}_{ff}$ is estimated. The stock returns are 25 Fama-French portfolios sorted by size and book-to-market, 10 momentum portfolios (2-12) and 30 industry portfolios. In Panel A, the risk factors are the Fama-French / Carhart factors and the factor mimicking portfolios for residential investment (RES) and business structures (BST). In Panel B, the risk factors are RES and BST and in addition portion of the SMB, HML, WML factors orthogonal to RES and BST (as described in Ferguson and Shockley (2003)). Estimation is by first-stage GMM using the identity matrix. T-statistics are reported in parentheses and are based on the Newey and West (1987) HAC covariance matrix with automatic lag length selection according to Andrews (1991). We report the cross-sectional OLS R^2, below the cross-sectional GLS R^2, the mean absolute error (MAE), and the Hansen-Jagannathan distance (HJ) with the simulation-based p-value for a test of a zero HJ. All data are monthly and the sample period is from January 1951 to December 2010.

Panel A:		Traditional Four-Factor Model and the GDP-based Model									
		γ	MKT	SMB	HML	WML	RES	BST	$R^{2\,OLS}_{GLS}$	MAE	HJ(pv)
(1)	$\boldsymbol{b}$	0.88	-1.04						0.02	0.17	0.44
		(3.89)	(-0.65)						0.01		(0.00)
	$\boldsymbol{\lambda}$		-0.20								
			(-0.65)								
(2)	$\boldsymbol{b}$	0.68	0.71	2.38	4.97	5.18			0.59	0.11	0.40
		(2.79)	(0.38)	(1.56)	(2.58)	(3.37)			0.24		(0.00)
	$\boldsymbol{\lambda}$		-0.04	0.12	0.22	0.72					
			(-0.13)	(1.04)	(1.79)	(4.35)					
(3)	$\boldsymbol{b}$	0.46	-0.94				6.32		0.46	0.12	0.39
		(1.82)	(-0.53)				(4.31)		0.26		(0.00)
	$\boldsymbol{\lambda}$		0.15				0.96				
			(0.45)				(3.92)				
(4)	$\boldsymbol{b}$	0.30	1.18				5.81	1.57	0.54	0.12	0.39
		(1.17)	(0.60)				(3.69)	(1.49)	0.26		(0.00)
	$\boldsymbol{\lambda}$		0.35				1.04	0.69			
			(1.09)				(4.43)	(2.48)			
Panel B:		SMB, HML and WML orthogonal to RES and BST									
		γ	MKT	SMB⊥	HML⊥	WML⊥	RES	BST	$R^{2\,OLS}_{GLS}$	MAE	HJ(pv)
(5)	$\boldsymbol{b}$	0.56	0.79	-6.91	20.49	30.49	5.35	1.50	0.66	0.10	0.38
		(2.30)	(0.24)	(-1.31)	(1.43)	(1.76)	(2.67)	(1.12)	0.33		(0.01)
	$\boldsymbol{\lambda}$		0.08	0.17	-0.14	0.19	0.95	0.68			
			(0.25)	(1.57)	(-1.26)	(2.05)	(4.40)	(2.42)			

Figure 1: Annual GDP Growth During Recessions

The figure shows the average growth rate of aggregate GDP and GDP components during 10 recessions between 1951 and 2010. GDP growth rates are annual, real and on a per capita basis. Vertical lines indicate one standard error confidence intervals. The beginning of recessions correspond to years with the value one on the horizontal axis and exhibit more than two recession quarters according to NBER. Accordingly, year zero is the peak of the cycle, year -1 is one year before, and so forth. In this figure, for a better comparison, the growth rates of aggregate GDP and GDP components are standardized by subtracting the mean and dividing by the standard deviation. Dotted lines in the graphs showing a GDP component correspond to aggregate GDP. The sample period is from 1951 to 2010.

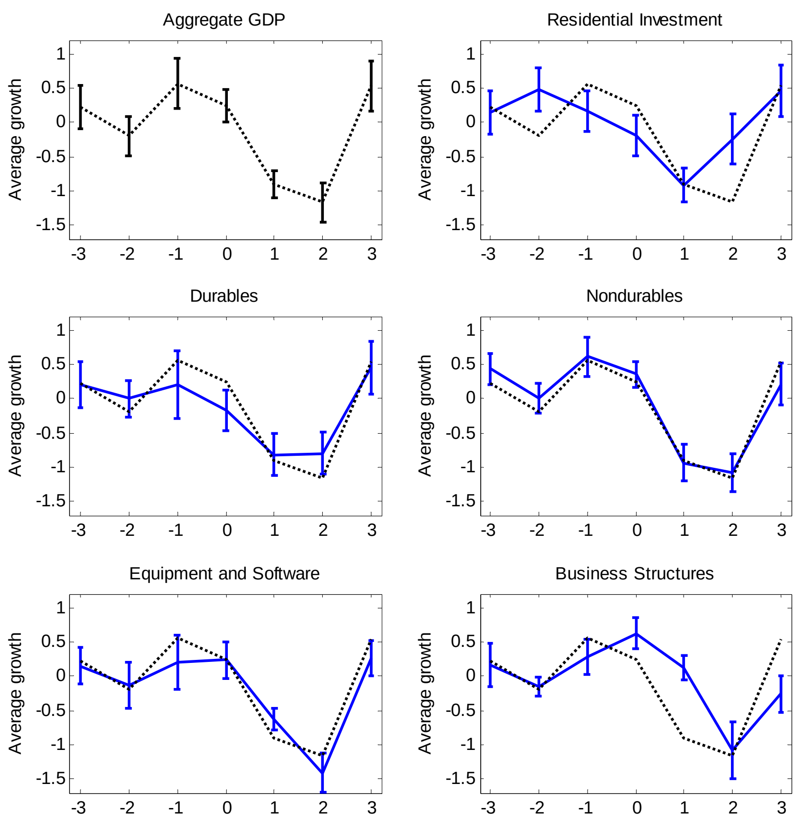


Figure 2: Mean-Variance Frontier and GDP Mimicking Portfolio Factors

The figure shows the mean-variance frontier of six Fama-French portfolios sorted by size and book-to-market and the momentum factor. RES is the mimicking portfolio of residential investment. DUR, NDU, EQS and BST are the analogous mimicking portfolios for durables, nondurables, equipment and software and business structures. The mimicking portfolios are based on the same assets which are represented by the mean-variance frontier. MKT is the market excess return. All data are monthly and the sample period is from January 1951 to December 2010.

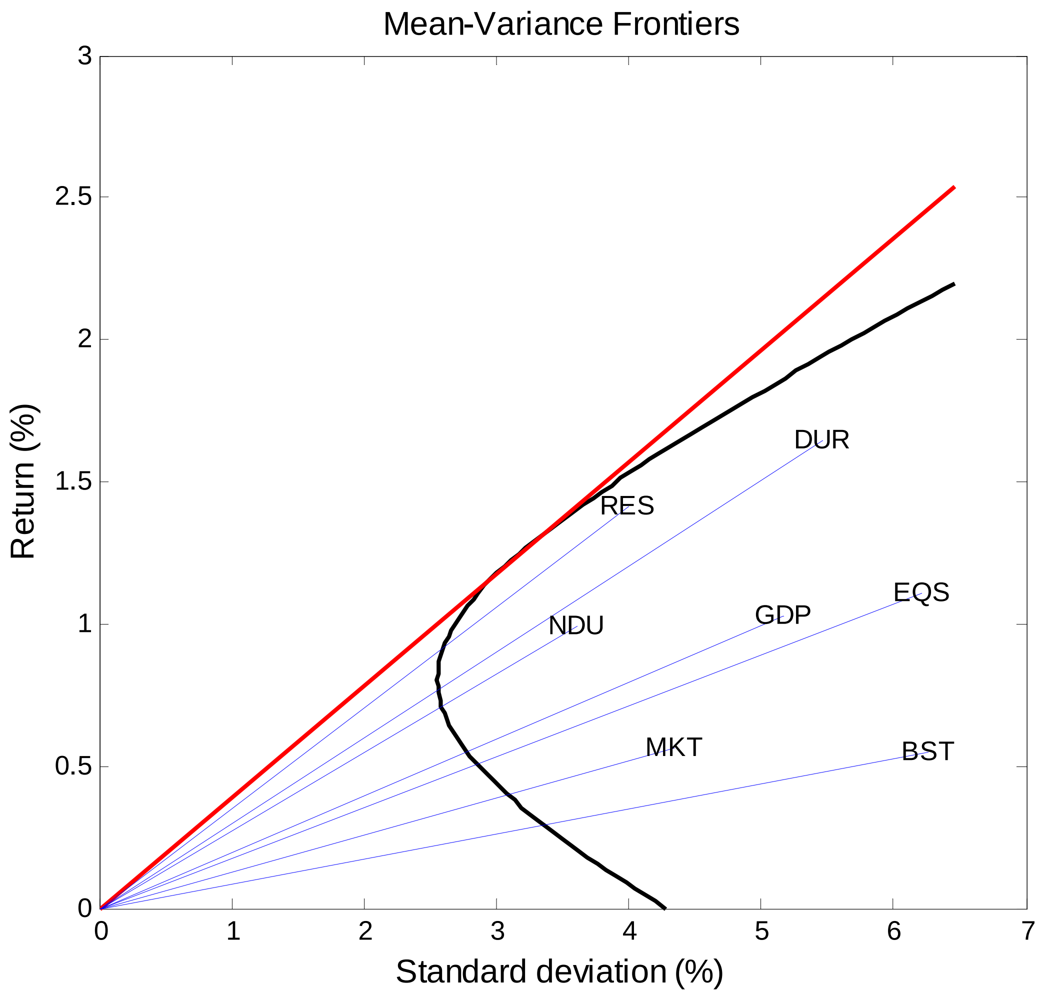


Figure 3: Predicted versus Realized Returns

The figure shows pricing errors for 25 Fama-French portfolios sorted by size and book-to-market and 10 momentum portfolios (2-12) using monthly GDP mimicking portfolios. GDP is aggregate GDP, RES is residential investment, BST is business structures, and MKT is the market excess return. All data are monthly and the sample period is from January 1951 to December 2010.

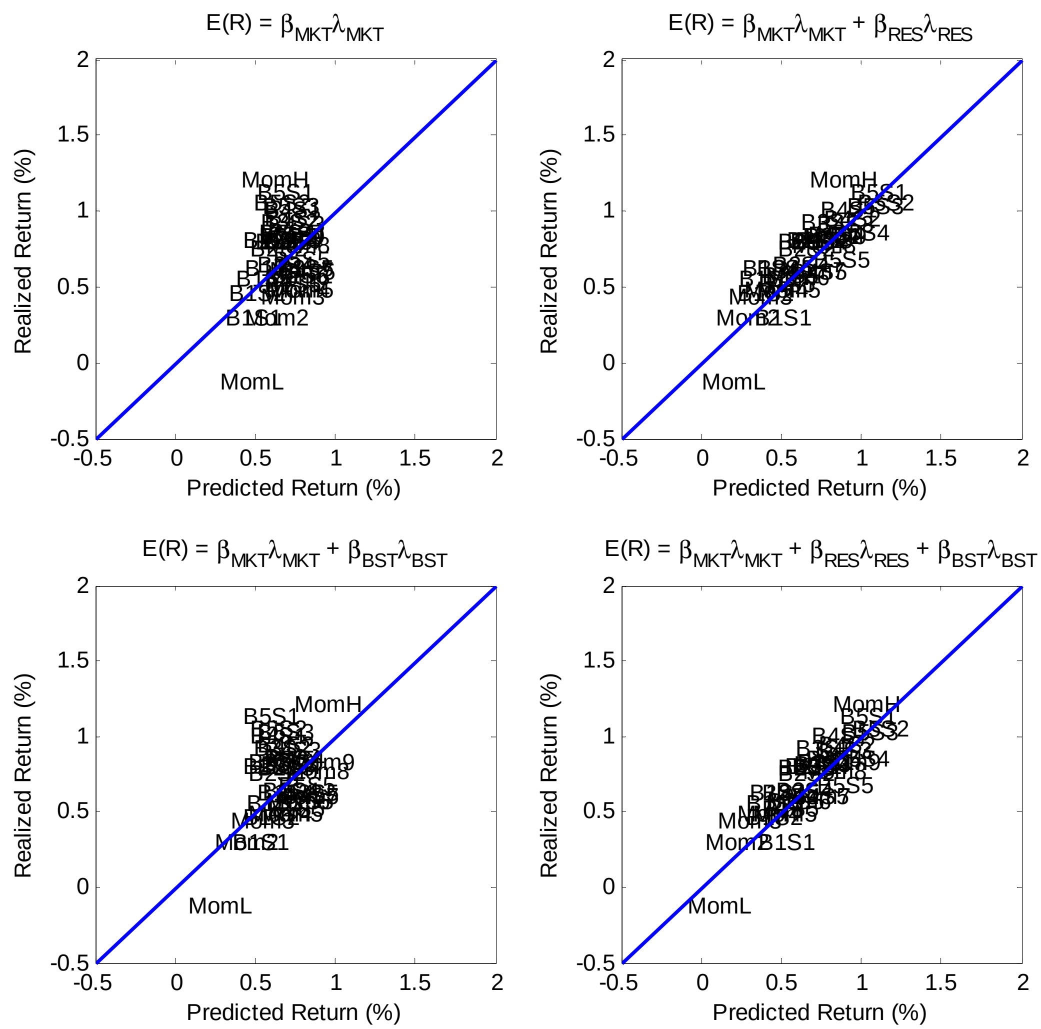


Figure 4: Cross-Section of 65 Equity Portfolios

The figure shows pricing errors for 25 Fama-French portfolios sorted by size and book-to-market, 10 momentum portfolios (2-12), and 30 industry portfolios using monthly GDP mimicking portfolios. RES is residential investment, BST is business structures, and MKT is the market excess return. The sample period is from January 1951 to December 2010.

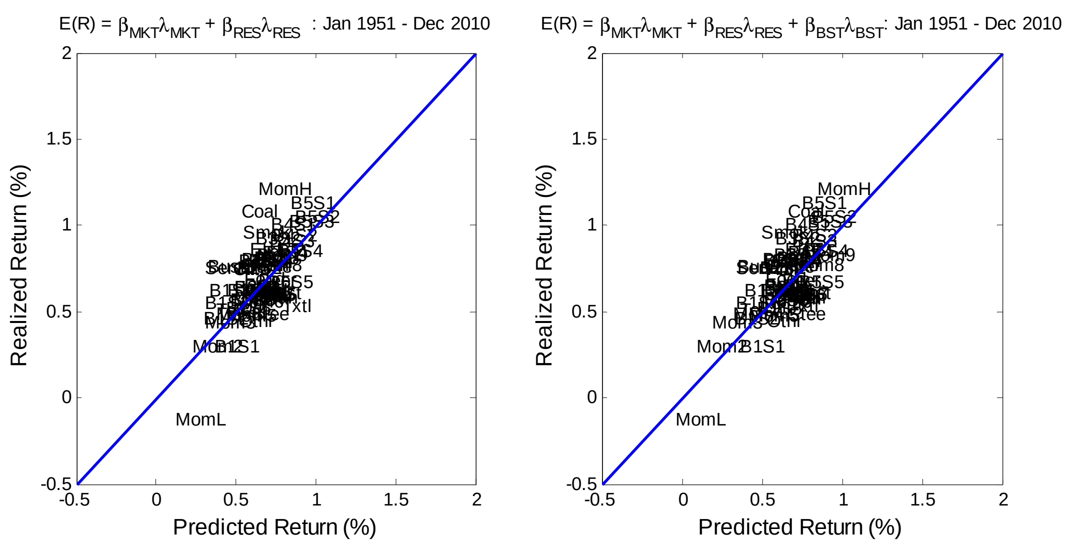


Table A.1: Monthly GDP Mimicking Portfolio Factors - Estimation without Intercept

The table reports GMM estimates of factor prices ($\boldsymbol{\lambda}$) of the monthly GDP mimicking portfolio factors as in the main paper but with a zero constant ($\gamma = 0$):

$$E\left(\mathbf{R}_t\right) = 0 + \boldsymbol{\beta}\boldsymbol{\lambda}.$$

T-statistics are reported in parentheses and are based on the Newey and West (1987) HAC covariance matrix with automatic lag length selection according to Andrews (1991). All data are monthly and the sample period is from January 1951 to December 2010.

	γ	Factor Price ($\boldsymbol{\lambda}$)		R^{2OLS}	γ	Factor Price ($\boldsymbol{\lambda}$)		R^{2OLS}	γ	Factor Price ($\boldsymbol{\lambda}$)			R^{2OLS}
	FF25				Momentum 10				FF25 + M10				
(1)	γ	MKT	RES		γ	MKT	RES		γ	MKT	RES		
	-	0.59	1.31	0.74	-	0.57	1.92	0.86	-	0.57	1.50		0.78
		(3.12)	(5.20)			(3.17)	(4.18)			(3.07)	(7.82)		
(2)	γ	MKT	DUR		γ	MKT	DUR		γ	MKT	DUR		
	-	0.73	2.37	0.72	-	0.62	1.63	0.88	-	0.70	1.93		0.77
		(3.75)	(4.19)			(3.49)	(3.97)			(3.75)	(6.20)		
(3)	γ	MKT	NDU		γ	MKT	NDU		γ	MKT	NDU		
	-	0.73	1.02	0.26	-	0.61	0.87	0.88	-	0.70	0.95		0.60
		(3.78)	(3.26)			(3.46)	(4.61)			(3.73)	(6.68)		
(4)	γ	MKT	EQS		γ	MKT	EQS		γ	MKT	EQS		
	-	0.79	0.90	-0.46	-	0.64	0.96	0.87	-	0.75	0.95		0.26
		(4.52)	(1.04)			(3.63)	(3.37)			(4.11)	(3.43)		
(5)	γ	MKT	BST		γ	MKT	BST		γ	MKT	BST		
	-	0.70	-0.38	-0.56	-	0.63	0.95	0.88	-	0.74	0.66		0.09
		(3.92)	(-0.62)			(3.61)	(3.15)			(4.09)	(2.42)		
(6)									γ	MKT	RES	BST	
									-	0.61	1.45	0.54	0.82
										(3.43)	(7.32)	(1.93)	

Table A.2: Annual Macroeconomic Variables

The table reports GMM estimates of a constant (γ) and factor prices ($\boldsymbol{\lambda}$) as in the main paper but we use annual real per capita growth rates of GDP components instead of the mimicking portfolios:

$$E\left(\mathbf{R}_t\right) = \gamma + \boldsymbol{\beta}\boldsymbol{\lambda}.$$

T-statistics are reported in parentheses and are based on the Newey and West (1987) HAC covariance matrix with automatic lag length selection according to Andrews (1991). All data are annual and the sample period is from 1951 to 2010.

	γ	Factor Price ($\boldsymbol{\lambda}$)		R^{2OLS}	γ	Factor Price ($\boldsymbol{\lambda}$)		R^{2OLS}	γ	Factor Price ($\boldsymbol{\lambda}$)			R^{2OLS}
	FF25				Momentum 10				FF25 + M10				
(1)	γ	MKT	RES		γ	MKT	RES		γ	MKT	RES		
	5.75	3.12	17.48	0.74	11.34	-2.78	28.16	0.39	8.19	0.50	19.18		0.57
	(0.87)	(0.47)	(2.49)		(1.06)	(-0.25)	(1.57)		(1.24)	(0.08)	(2.46)		
(2)	γ	MKT	DUR		γ	MKT	DUR		γ	MKT	DUR		
	4.92	5.34	10.83	0.48	8.27	0.82	17.11	0.76	5.66	4.28	13.52		0.53
	(0.67)	(0.71)	(2.13)		(1.12)	(0.11)	(1.52)		(0.80)	(0.58)	(3.03)		
(3)	γ	MKT	NDU		γ	MKT	NDU		γ	MKT	NDU		
	5.87	4.24	1.66	0.25	3.99	5.35	2.42	0.89	3.88	5.96	2.27		0.58
	(1.21)	(0.87)	(1.68)		(0.71)	(0.93)	(1.63)		(0.69)	(1.03)	(1.82)		
(4)	γ	MKT	EQS		γ	MKT	EQS		γ	MKT	EQS		
	17.47	-9.05	-9.44	0.21	6.96	2.41	11.33	0.96	10.04	0.46	5.69		0.15
	(2.22)	(-1.24)	(-1.33)		(1.68)	(0.54)	(2.00)		(2.38)	(0.10)	(1.84)		
(5)	γ	MKT	BST		γ	MKT	BST		γ	MKT	BST		
	20.63	-12.19	-10.89	0.54	1.21	8.05	10.32	0.90	11.50	-1.62	2.41		0.06
	(2.08)	(-1.26)	(-1.95)		(0.26)	(1.42)	(1.86)		(2.69)	(-0.34)	(0.97)		
(6)									γ	MKT	RES	BST	
									3.63	5.59	20.72	3.40	0.64
									(0.54)	(0.76)	(2.13)	(0.71)	

Table A.3: Annual Macroeconomic Variables - Estimation without Intercept

The table reports GMM estimates of factor prices ($\boldsymbol{\lambda}$) as in the main paper but we use annual real per capita growth rates of GDP components and impose a zero constant ($\gamma = 0$):

$$E\left(\mathbf{R}_t\right) = 0 + \boldsymbol{\beta}\boldsymbol{\lambda}.$$

T-statistics are reported in parentheses and are based on the Newey and West (1987) HAC covariance matrix with automatic lag length selection according to Andrews (1991). All data are annual and the sample period is from 1951 to 2010.

	γ	Factor Price ($\boldsymbol{\lambda}$)		R^{2OLS}	γ	Factor Price ($\boldsymbol{\lambda}$)		R^{2OLS}	γ	Factor Price ($\boldsymbol{\lambda}$)			R^{2OLS}
	FF25				Momentum 10				FF25 + M10				
(1)	γ	MKT	RES		γ	MKT	RES		γ	MKT	RES		
	-	8.29	20.01	0.66	-	8.39	43.61	0.19	-	7.97	22.94		0.45
		(4.11)	(2.66)			(3.67)	(1.16)			(3.99)	(2.70)		
(2)	γ	MKT	DUR		γ	MKT	DUR		γ	MKT	DUR		
	-	9.95	12.44	0.43	-	8.93	20.52	0.65	-	9.64	15.44		0.48
		(3.21)	(1.89)			(4.44)	(1.64)			(3.70)	(2.89)		
(3)	γ	MKT	NDU		γ	MKT	NDU		γ	MKT	NDU		
	-	9.73	2.12	0.19	-	9.33	2.67	0.87	-	9.64	2.51		0.56
		(4.03)	(1.94)			(4.87)	(1.65)			(4.70)	(2.08)		
(4)	γ	MKT	EQS		γ	MKT	EQS		γ	MKT	EQS		
	-	8.93	-2.12	-0.37	-	9.24	12.37	0.88	-	10.39	7.96		-0.01
		(3.93)	(-0.52)			(4.93)	(2.07)			(5.08)	(2.43)		
(5)	γ	MKT	BST		γ	MKT	BST		γ	MKT	BST		
	-	8.27	-5.14	-0.28	-	9.27	10.57	0.90	-	9.76	5.09		-0.12
		(3.99)	(-1.27)			(3.94)	(1.76)			(4.17)	(1.79)		
(6)									γ	MKT	RES	BST	
									-	9.15	22.25	4.20	0.63
										(4.55)	(2.50)	(0.95)	

Online Appendix to Accompany

GDP Mimicking Portfolios and the Cross-Section of Stock Returns

April 5, 2013

Additional Results for Section 2

In Section 2 of the main text, we base our analyzes on the empirical fact that some GDP components lead aggregate GDP and some GDP components lag aggregate GDP. This stylized pattern of the data can be also illuminated using the event-based approach proposed by Koijen, Lustig, and Nieuwerburgh (2012).

First, we define an event as the lowest 30% realizations of a specific time series, e.g. aggregate GDP, and label this event '0'. Second, we pick dates prior ('-1', '-2', '-3') and dates following ('1', '2, '3') the event. Third, we plot the average realization of a specific variable (e.g., growth of residential investment) during this event time line.

Lead and Lag in GDP Components. Figure OA.1 provides annual real per capita aggregate GDP and the five GDP components in aggregate GDP-event time. For comparisons, Figure OA.2 shows aggregate GDP and the five GDP components during NBER recessions. We find in both figures that the lead-lag behavior of GDP components shows up.

Forecasting Regressions with Non-standardized GDP. Table OA.1 provides forecasting regressions of aggregate GDP on one period lagged components of GDP. In difference to the main text, we do not standardize the variables.

Table OA.1: Forecasting Regressions with Non-standardized GDP

The table provides forecasting regressions of aggregate GDP on one period lagged components of GDP as in the main paper, except that the variables are not standardized. Newey-West corrected t-statistics are reported in brackets (automatic lag length selection). All data are annual and the sample period is from 1951 to 2010.

Forecasting regressions for real per capita growth rates:

$$\triangle GDP_t = \alpha + \beta \, \triangle Y_{j,t-1} + \epsilon_t$$

	α	$t\,(\alpha)$	β	$t\,(\beta)$	R^2
GDP	1.74	[4.43]	0.10	[0.75]	0.01
RES	1.88	[7.97]	0.08	[5.06]	0.20
DUR	1.67	[4.62]	0.07	[1.41]	0.04
NDU	0.87	[1.47]	0.54	[2.28]	0.09
EQS	1.97	[5.87]	-0.01	[-0.22]	0.00
BST	2.01	[7.30]	-0.07	[-1.88]	0.06

Figure OA.1: Low Aggregate GDP Events

The figure shows annual real per capita growth of aggregate GDP and five GDP components in aggregate GDP event time. The event is defined as years with the 30% lowest realizations of aggregate GDP growth and is labeled '0'. The years '-1', '-2, and '-3' refer to one, two, and three years before the event takes place. The years '1', '2, and '3' refer to one, two, and three years after the event takes place. The panels plot aggregate GDP (GDP), residential investment (RES), durables (DUR), nondurables (NDU), equipment and software (EQS) and business structures (BST), and the sample is from 1951 to 2010.

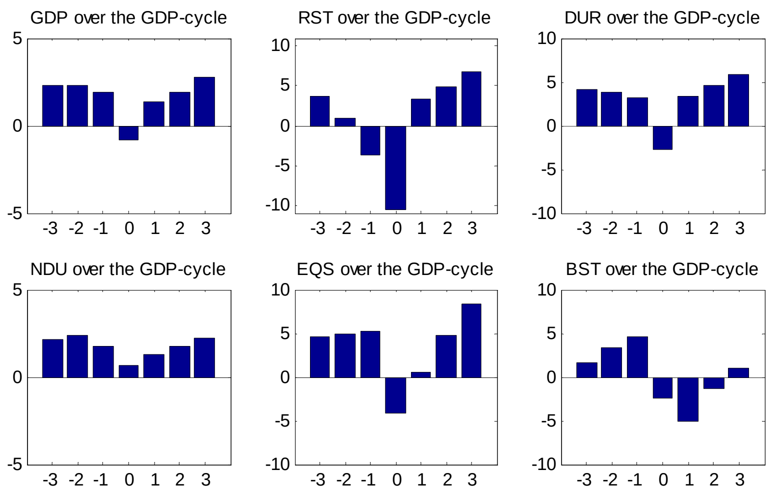
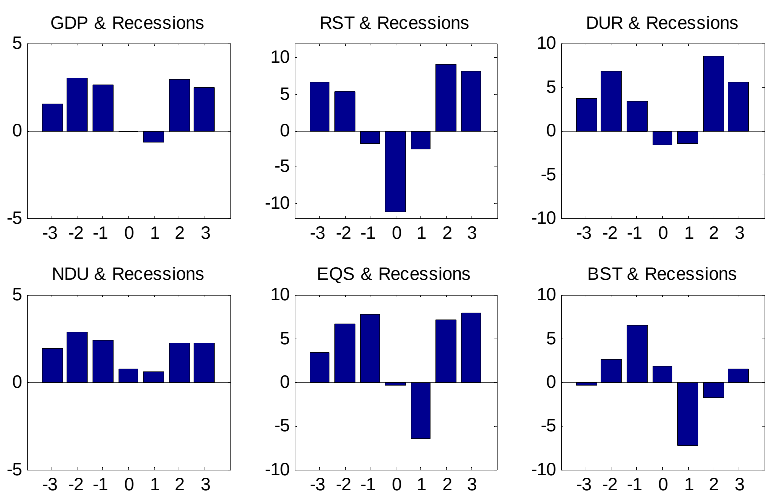


Figure OA.2: Recession Events

The figure shows annual real per capita growth of aggregate GDP and five GDP components during recessions. The beginning of a recession year is defined as a year with more than two recession quarters according to NBER and is labeled '0'. The sample is from 1951 to 2010.



Additional Results for Section 3

Low GDP Events and Stock Market Returns. We find in the main text, that mimicking portfolio factors of leading GDP components significantly load on the book-to-market factor (HML), and that mimicking portfolio factors of lagging GDP components significantly load on the momentum factor (WML). This pattern is visualized in Figure OA.3 using the event time approach. We show MKT, SMB, HML, and WML in aggregate GDP and GDP components-event time. Low realizations of residential investment growth correspond to low HML returns. Low realizations of business structures growth correspond to low momentum returns.

Stock Market Crashes and GDP Components. Figure OA.4 shows aggregate GDP and five GDP components during stock market "crashes". We distinguish between general stock market crashes measured by MKT, size crashes measured by SMB, value crashes measured by HML, and momentum crashes measured by WML.

The GDP-based Three-Factor Model in one Picture. Figure OA.5 provides a close-up view for residential investment and business structures during value and momentum crashes. Value crashes coincide with low realizations of residential investment growth. Momentum crashes coincide with low realizations of business structures growth.

Additional Results for Section 5

25 Size / Momentum Portfolios. In the main paper, we study 25 Fama-French portfolios sorted on size and book-to-market, and 10 momentum portfolios. As an alternative, we consider 25 portfolios sorted on size and momentum in Table OA.2. We find that all GDP mimicking portfolio factors have a positive risk premium. Overall, the leading GDP components have a better model fit than the lagging GDP components. When we add business structures to residential investment (specification 8) the factor risk premium for BST is significant and the model fit is further improved.

25 Fama-French or 10 Momentum Portfolios. How does the GDP-based three factor model perform on 25 Fama-French *or* 10 momentum portfolios? Table OA.3 shows that the slope coefficient for BST is negative and insignificant if we include only 25 Fama-French portfolios. In contrast, the slope coefficient for RES is positive and significant. Results are vice versa if we include only 10 momentum portfolios.

This finding is not surprising. The main text shows that the growth rate of leading GDP component covaries only little with the momentum portfolios, and that the growth rate of lagging GDP component covaries only little with the 25 Fama-French portfolios. Thus, momentum portfolios are not informative for SDF loadings and factor prices of leading GDP components and vice versa.

Figure OA.3: Low GDP Events and Stock Market Returns

The figure shows annual real returns for the market premium (MKT), the size premium (SMB) the book-to-market premium (HML) and the momentum premium (WML) in event time. The event is defined as years with the 30% lowest realizations of GDP growth and is labeled '0'. The years '-1', '-2, and '-3' refer to one, two, and three years before the event takes place. The years '1', '2, and '3' refer to one, two, and three years after the event takes place. The panels plot event time for aggregate GDP (GDP), residential investment (RES), durables (DUR), nondurables (NDU), equipment and software (EQS) and business structures (BST). The sample is from 1951 to 2010.

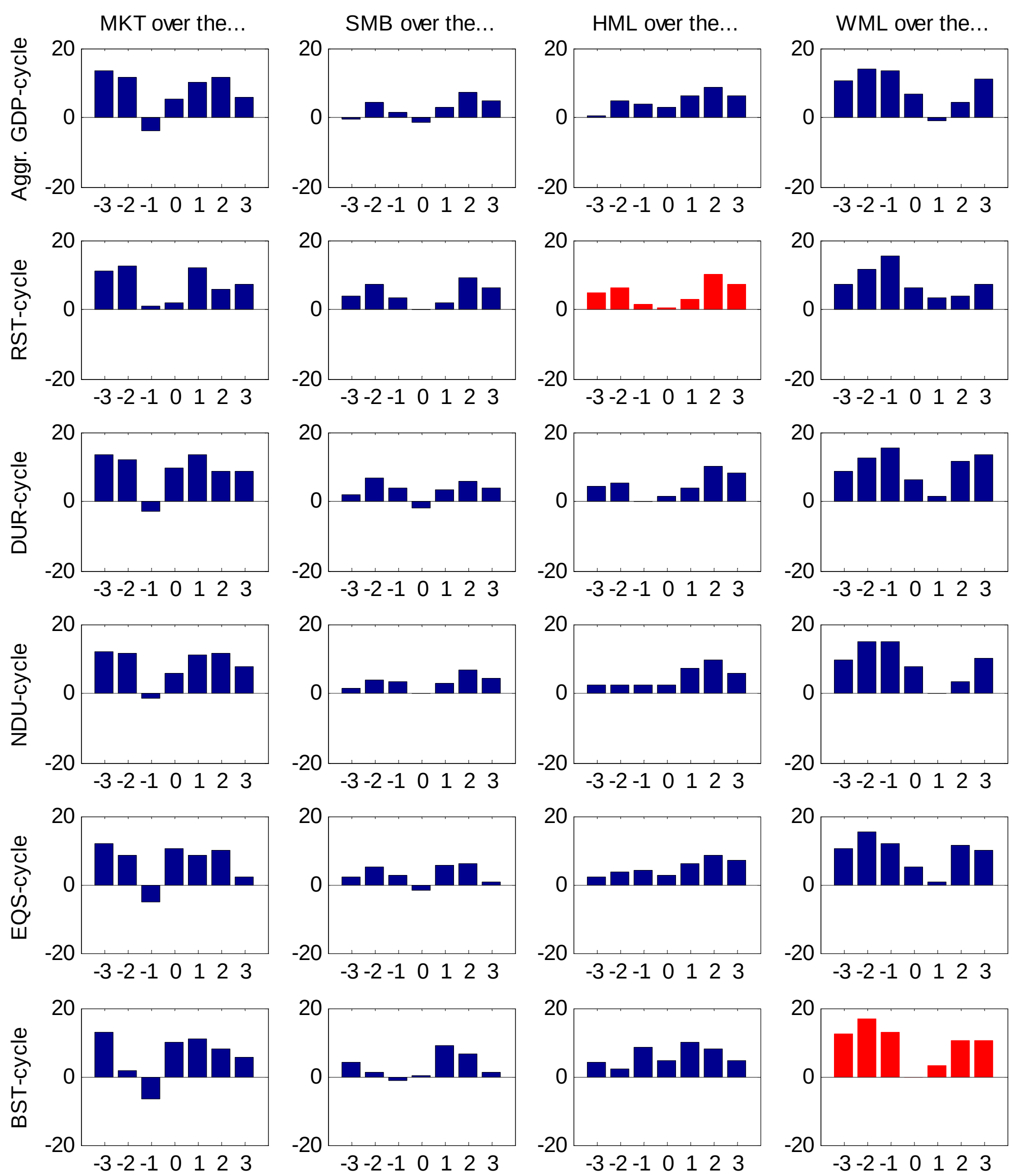


Figure OA.4: Stock Market Crashes

The figure shows annual real per capita growth of aggregate GDP and five GDP components during stock market crashes. A stock market crash is defined as years with the 30% lowest realizations of returns and is labeled '0'. The years '-1', '-2, and '-3' refer to one, two, and three years before the event takes place. The years '1', '2, and '3' refer to one, two, and three years after the event takes place. The panels plot stock market crashes for the market premium (MKT), the size premium (SMB) the book-to-market premium (HML) and the momentum premium (WML). The sample is from 1951 to 2010.

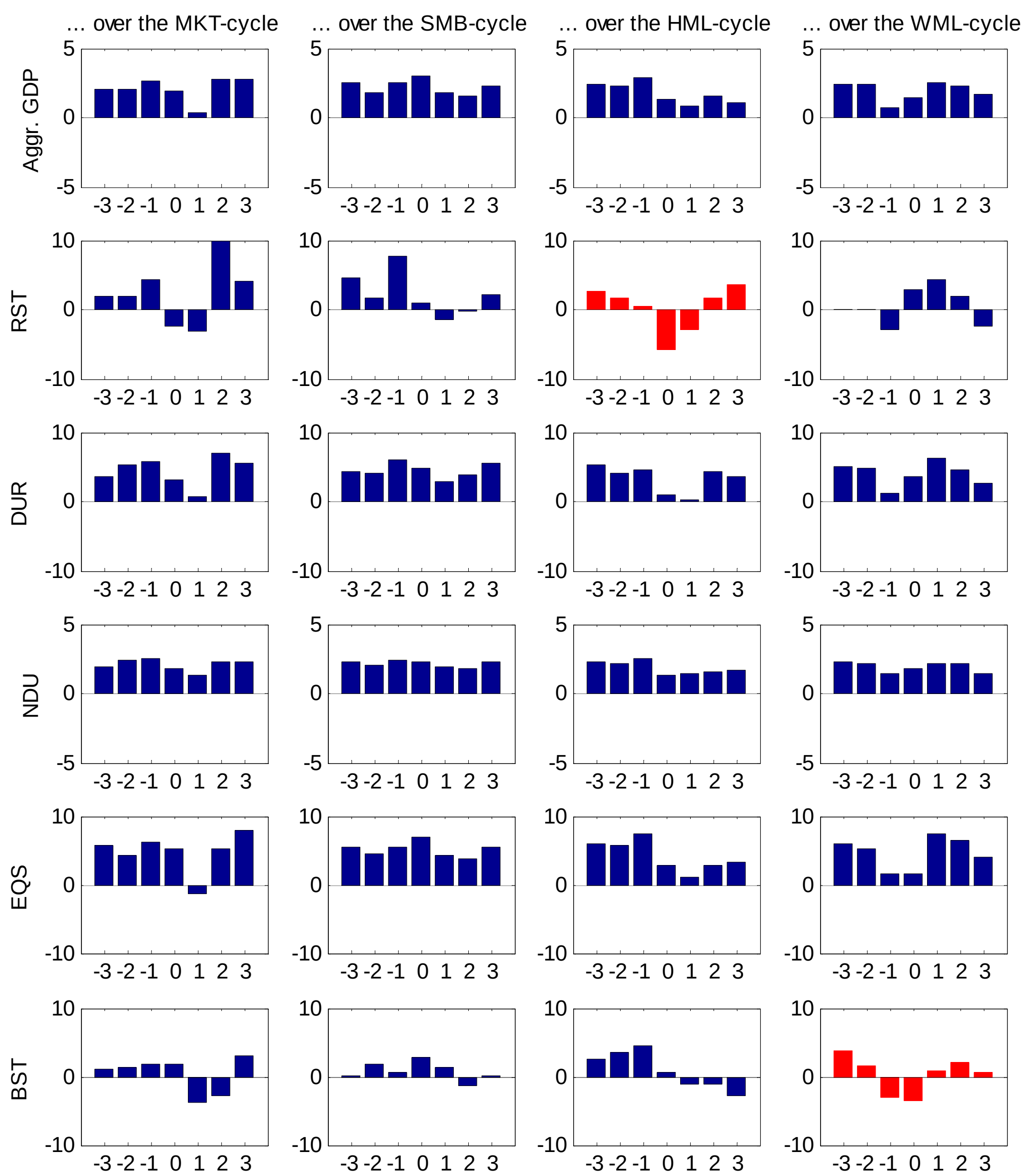


Figure OA.5: Value and Momentum Crashes

The figure shows annual real per capita growth of residential investment (RST) and business structures (BST) during book-to-market (HML) and momentum (WML) crashes. A stock market crash event is defined as years with the 30% lowest realizations of returns and is labeled '0'. The years '-1', '-2, and '-3' refer to one, two, and three years before the event takes place. The years '1', '2, and '3' refer to one, two, and three years after the event takes place. The sample is from 1951 to 2010.

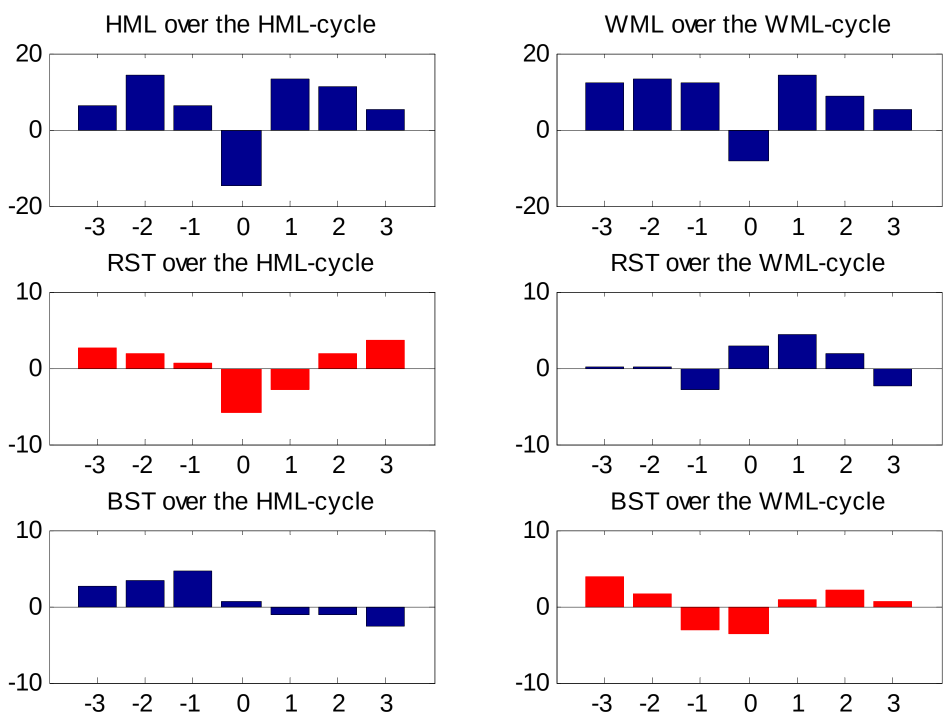


Table OA.2: GDP Mimicking Factors: Size / Momentum 25

The table reports GMM estimates of factor prices (λ) and SDF loadings (b) of the monthly GDP mimicking portfolio factors as described in the main paper. This table shows results for 25 double sorted size and momentum portfolios. T-statistics are reported in parentheses and are based on the Newey and West (1987) HAC covariance matrix with automatic lag length selection according to Andrews (1991). All data are monthly and the sample period is from January 1951 to December 2010.

	Const	SDF Loadings (b)			Factor Prices (λ)			R^{2OLS}_{GLS}	MAE	HJ(pv)
(1)	γ	MKT			MKT					
	1.56	-4.11			-0.77			0.10	0.28	0.36
	(5.49)	(-2.14)			(-2.14)			0.02		(0.00)
(2)	γ	MKT	GDP		MKT	GDP				
	0.27	5.34	5.05		0.58	0.90		0.68	0.16	0.33
	(1.07)	(2.63)	(3.48)		(1.81)	(3.80)		0.18		(0.00)
(3)	γ	MKT	RES		MKT	RES				
	-0.20	0.32	13.94		0.78	2.24		0.85	0.11	0.33
	(-0.44)	(0.12)	(3.59)		(1.62)	(3.97)		0.21		(0.00)
(4)	γ	MKT	DUR		MKT	DUR				
	-0.08	6.11	7.47		0.84	1.98		0.83	0.12	0.32
	(-0.22)	(2.43)	(3.56)		(2.10)	(4.29)		0.23		(0.00)
(5)	γ	MKT	NDU		MKT	NDU				
	0.03	4.50	8.39		0.76	1.05		0.76	0.14	0.33
	(0.11)	(2.24)	(3.54)		(2.22)	(4.79)		0.20		(0.00)
(6)	γ	MKT	EQS		MKT	EQS				
	0.44	4.54	4.23		0.42	1.17		0.72	0.15	0.33
	(1.69)	(2.27)	(3.49)		(1.30)	(3.88)		0.19		(0.00)
(7)	γ	MKT	BST		MKT	BST				
	0.51	4.23	3.90		0.37	1.07		0.61	0.18	0.34
	(2.23)	(2.39)	(3.34)		(1.27)	(3.47)		0.14		(0.00)
(8)	γ	MKT	RES	BST	MKT	RES	BST			
	-0.22	2.23	11.32	1.28	0.86	1.97	0.65	0.88	0.10	0.32
	(-0.52)	(1.20)	(3.14)	(1.00)	(2.03)	(3.49)	(1.96)	0.23		(0.00)

Table OA.3: The GDP-based Model: Fama-French 25 or Momentum 10

The table reports GMM estimates of factor prices (λ) and SDF loadings (b) of the monthly GDP-based three factor model as described in the main paper. This table shows results for 25 Fama-French portfolios and 10 momentum portfolios, separately, with and without intercept. T-statistics are reported in parentheses and are based on the Newey and West (1987) HAC covariance matrix with automatic lag length selection according to Andrews (1991). All data are monthly and the sample period is from January 1951 to December 2010.

		γ	Factor Price (λ)			R^{2OLS}	γ	Factor Price (λ)			R^{2OLS}
		Fama-French 25					Momentum 10				
(1)		γ	MKT	RES	BST		γ	MKT	RES	BST	
	b	1.12	-6.03	4.86	-3.41	0.82	1.80	15.11	-40.14	15.49	0.94
		(3.30)	(-2.49)	(2.43)	(-1.55)		(1.54)	(1.58)	(-1.64)	(2.01)	
	λ		-0.51	0.35	-0.51	0.82		-0.91	-5.09	3.05	0.94
			(-1.41)	(0.81)	(-0.69)			(-0.83)	(-1.52)	(2.23)	
		Const	MKT	RES	BST		Const	MKT	RES	BST	
(2)	b	-	0.98	7.88	0.00	0.74	-	4.27	2.93	3.07	0.88
			(0.73)	(4.47)	(0.00)			(1.05)	(0.38)	(1.11)	
	λ		0.59	1.31	0.16	0.74		0.62	0.79	0.84	0.88
			(3.40)	(4.27)	(0.24)			(3.34)	(0.85)	(1.96)	

News Related to Future GDP

Vassalou (2003). We reconsider how important the lead and lag structure, or the timing, coherent in the GDP components actually is. Vassalou (2003) finds that a "news related to *future* GDP" mimicking portfolio can explain the cross-section of size/book-to-market portfolios. The weights for Vassalou's mimicking portfolio factor are found by regressing the aggregate GDP growth rate of the *next* year on asset returns of the *current* year.

Design. We investigate the importance of timing by constructing modified GDP mimicking portfolios which take the lead and lag structure into account. More precisely, we estimate mimicking portfolio weights as in Equation (OA.4), except that we use the growth rate of aggregate GDP measured in $t + 1$, residential investment in t, durables in $t + 1$, nondurables in $t+1$, equipment and software in $t+1$, and business structures in $t+2$. This timing mainly eliminates the lead of residential investment and durables compared to all other variables at the annual frequency.

Results. Table OA.4 reports the results for the Fama-French portfolios. Since we need future GDP variables (up to $t + 2$) we use only asset return data from 1951 to 2008 for all seven specifications. After accounting for lead and lags, aggregate GDP as well as all five GDP components capture a substantial fraction of the cross-sectional variation in average returns.

We find that the specification with contemporaneous residential investment slightly outperforms future aggregate GDP (Vassalou (2003)). The constant for future aggregate GDP is about twice as large as for residential investment (8.5% vs 4.3%); only the SDF loading is significant (and positive) but not the risk factor price. Both models have approximately equal OLS R^2s (0.82 vs 0.83). Note that after controlling for their lag, equipment and software as well as business structures show economically plausible positive point estimates for the SDF loadings and risk factor prices.

Table OA.4: News Related to Future GDP: Fama-French 25

The table reports GMM estimates of a constant (γ), SDF loadings ($\mathbf{b}$), and factor prices ($\boldsymbol{\lambda}$) as in the main paper. The risk factors are the excess return on the market portfolio (MKT), and factor mimicking portfolios for contemporaneous period residential investment (RES), next period aggregate GDP (L^{-1}GDP), durables (L^{-1}DUR), nondurables (L^{-1}NDU), equipment and software (L^{-1}EQS), and two period ahead business structures (L^{-2}BST). Thus, the GDP mimicking portfolios control for lags to residential investment. The stock returns are 25 Fama-French portfolios sorted by size and book-to-market. All data are annual and the sample period is from 1951 to 2008/2010.

	Const	SDF Loadings ($\mathbf{b}$)		Factor Prices ($\boldsymbol{\lambda}$)		R^{2OLS}	MAE	HJ(pv)
(1)	γ	MKT	L^{-1}GDP	MKT	L^{-1}GDP			
	8.53	-6.88	6.39	-1.54	3.33	0.82	0.87	0.75
	(1.29)	(-1.75)	(2.60)	(-0.22)	(0.47)			(0.12)
(2)	γ	MKT	L^0RES	MKT	L^0RES			
	4.30	-0.64	1.10	2.99	34.44	0.83	0.88	0.73
	(0.70)	(-0.26)	(2.58)	(0.44)	(2.41)			(0.21)
(3)	γ	MKT	L^{-1}DUR	MKT	L^{-1}DUR			
	5.30	-2.73	3.57	1.88	10.72	0.82	0.92	0.74
	(0.91)	(-1.02)	(2.56)	(0.29)	(1.58)			(0.14)
(4)	γ	MKT	L^{-1}NDU	MKT	L^{-1}NDU			
	13.51	-7.58	4.60	-6.23	4.14	0.84	0.88	0.74
	(1.81)	(-1.77)	(2.44)	(-0.79)	(0.46)			(0.14)
(5)	γ	MKT	L^{-1}EQS	MKT	L^{-1}EQS			
	4.51	-4.93	7.25	3.15	8.53	0.75	1.07	0.75
	(0.72)	(-1.49)	(2.63)	(0.46)	(1.37)			(0.11)
(6)	γ	MKT	L^{-2}BST	MKT	L^{-2}BST			
	18.56	-8.04	3.66	-10.69	4.96	0.56	1.45	0.77
	(1.93)	(-2.14)	(2.58)	(-1.15)	(0.45)			(0.06)

Subsamples and Out-of-sample Estimation

Subsamples. We want to make sure that our cross-sectional regressions are not driven by a few occasional "outlier" or one particular event like the recent financial crisis. We estimate the mimicking portfolio weights using the full sample from 1951 to 2010, as in the main text. Following, we split our sample in two distinct subsamples from 1951 to 1980 and 1981 to 2010. Table OA.5 and Table OA.6 provide the cross-sectional slope coefficients for both subsamples. We find very similar results in both subsamples which are comparable to the full sample results in the main text.

Out-of-sample. We also study the stability of our mimicking portfolio factor weights in a challenging out-of-sample setup in Table OA.7. We use the first 30 years of annual data (1951 to 1980) to calculate the monthly mimicking portfolio factors of the twelve months in the following year (1981). Following, we expand the estimation window by one year, and repeat for the next 12 months.

Thus, the mimicking portfolio factors use real time information only when running cross-sectional tests for the period 1981 to 2010 in Table OA.7. We find that the resulting portfolio weights are very noisy when only a few observations are available (approximately less than 40 annual observations), but quickly stabilize for the further expanding samples. In this light, it is remarkable that the out-of-sample/expanding window results in Table OA.7 are still comparable to the full sample results presented in the main text.

Table OA.5: Subsample: 1951 to 1980

The table reports GMM estimates of a constant (γ) and factor prices ($\boldsymbol{\lambda}$) as in the main paper, except that we use only use the first 30 years for the cross-sectional regressions (January 1951 to December 1980). T-statistics are reported in parentheses and are based on the Newey and West (1987) HAC covariance matrix with automatic lag length selection according to Andrews (1991).

	γ	Factor Price ($\boldsymbol{\lambda}$)		R^{2OLS}	γ	Factor Price ($\boldsymbol{\lambda}$)		R^{2OLS}	γ	Factor Price ($\boldsymbol{\lambda}$)			R^{2OLS}
	Fama-French 25				Momentum 10				Fama-French 25 + Mom. 10				
(1)	γ	MKT	RES		γ	MKT	RES		γ	MKT	RES		
	0.39	0.29	0.81	0.65	0.62	0.04	3.04	0.89	0.33	0.28	1.18		0.55
	(0.78)	(0.50)	(2.08)		(1.01)	(0.06)	(2.69)		(0.71)	(0.50)	(3.15)		
(2)	γ	MKT	DUR		γ	MKT	DUR		γ	MKT	DUR		
	0.09	0.68	1.31	0.45	0.10	0.57	2.56	0.90	-0.25	0.98	2.10		0.68
	(0.16)	(1.12)	(2.87)		(0.20)	(1.01)	(4.02)		(-0.47)	(1.60)	(5.53)		
(3)	γ	MKT	NDU		γ	MKT	NDU		γ	MKT	NDU		
	-0.16	0.89	0.72	0.21	0.19	0.47	1.12	0.92	-0.53	1.21	1.13		0.68
	(-0.29)	(1.39)	(1.79)		(0.42)	(0.90)	(4.93)		(-0.99)	(1.93)	(5.55)		
(4)	γ	MKT	EQS		γ	MKT	EQS		γ	MKT	EQS		
	1.27	-0.61	-1.16	0.19	0.05	0.61	1.33	0.92	-0.19	0.98	0.84		0.41
	(1.93)	(-0.89)	(-1.40)		(0.10)	(1.15)	(3.83)		(-0.39)	(1.68)	(2.38)		
(5)	γ	MKT	BST		γ	MKT	BST		γ	MKT	BST		
	1.80	-1.10	-1.23	0.48	0.10	0.55	1.42	0.93	-0.26	1.00	0.59		0.30
	(2.83)	(-1.72)	(-1.90)		(0.23)	(1.05)	(3.68)		(-0.53)	(1.78)	(1.56)		
(6)									γ	MKT	RES	BST	
									-0.25	0.91	1.49	0.68	0.75
									(-0.52)	(1.59)	(3.78)	(1.82)	

Table OA.6: Subsample: 1981 to 2010

The table reports GMM estimates of a constant (γ) and factor prices ($\boldsymbol{\lambda}$) as in the main paper, except that we use only use the last 30 years for the cross-sectional regressions (January 1981 to December 2009). T-statistics are reported in parentheses and are based on the Newey and West (1987) HAC covariance matrix with automatic lag length selection according to Andrews (1991).

	γ	Factor Price ($\boldsymbol{\lambda}$)		R^{2OLS}	γ	Factor Price ($\boldsymbol{\lambda}$)		R^{2OLS}	γ	Factor Price ($\boldsymbol{\lambda}$)			R^{2OLS}
	Fama-French 25				Momentum 10				Fama-French 25 + Mom. 10				
(1)	γ	MKT	RES		γ	MKT	RES		γ	MKT	RES		
	0.32	0.28	1.32	0.67	0.51	0.05	0.92	0.67	0.34	0.25	1.23		0.68
	(0.44)	(0.34)	(2.17)		(0.84)	(0.08)	(1.20)		(0.53)	(0.35)	(2.55)		
(2)	γ	MKT	DUR		γ	MKT	DUR		γ	MKT	DUR		
	0.25	0.46	3.00	0.71	0.69	-0.10	0.94	0.70	0.89	-0.20	1.34		0.57
	(0.34)	(0.56)	(3.74)		(1.43)	(-0.19)	(1.56)		(1.43)	(-0.30)	(2.52)		
(3)	γ	MKT	NDU		γ	MKT	NDU		γ	MKT	NDU		
	1.57	-0.83	0.40	0.39	0.61	-0.03	0.54	0.69	1.00	-0.30	0.59		0.45
	(3.00)	(-1.63)	(0.59)		(1.21)	(-0.05)	(1.58)		(1.57)	(-0.46)	(1.93)		
(4)	γ	MKT	EQS		γ	MKT	EQS		γ	MKT	EQS		
	1.75	-0.97	1.46	0.39	0.83	-0.23	0.83	0.71	1.45	-0.73	1.03		0.43
	(3.10)	(-1.59)	(1.65)		(1.98)	(-0.44)	(1.70)		(3.01)	(-1.33)	(2.20)		
(5)	γ	MKT	BST		γ	MKT	BST		γ	MKT	BST		
	2.45	-1.84	-0.83	0.59	0.75	-0.15	0.79	0.71	1.58	-0.87	0.80		0.36
	(3.97)	(-2.76)	(-0.65)		(1.72)	(-0.28)	(1.67)		(3.12)	(-1.55)	(1.82)		
(6)									γ	MKT	RES	BST	
									0.38	0.19	1.25	0.39	0.70
									(0.55)	(0.26)	(2.56)	(0.81)	

Table OA.7: Out-of-sample: Expanding Window

The table reports GMM estimates of a constant (γ) and factor prices ($\boldsymbol{\lambda}$) as in the main paper, except that we use a rolling window to estimate the GDP mimicking portfolio weights and run cross-sectional regressions "out-of-sample". We use the first 30 years of annual data (1951 to 1980) to calculate the monthly mimicking portfolio factors of the twelve months in the following year (1981). We expand the estimation window by one year, and repeat for the next 12 months. The table reports cross-sectional regressions of the out-of-sample generated monthly factor mimicking portfolios from January 1981 to December 2010. T-statistics are reported in parentheses and are based on the Newey and West (1987) HAC covariance matrix with automatic lag length selection according to Andrews (1991).

	γ	Factor Price ($\boldsymbol{\lambda}$)		R^{2OLS}	γ	Factor Price ($\boldsymbol{\lambda}$)		R^{2OLS}	γ	Factor Price ($\boldsymbol{\lambda}$)			R^{2OLS}
	FF25				Momentum 10				FF25 + M10				
(1)	γ	MKT	RES		γ	MKT	RES		γ	MKT	RES		
	0.68	-0.07	0.29	0.60	1.28	-0.63	-0.28	0.75	1.62	-0.95	0.00		0.35
	(0.97)	(-0.09)	(1.99)		(2.53)	(-1.07)	(-1.32)		(3.53)	(-1.73)	(0.04)		
(2)	γ	MKT	DUR		γ	MKT	DUR		γ	MKT	DUR		
	0.60	0.04	0.33	0.76	0.69	-0.11	0.16	0.68	0.75	-0.10	0.23		0.67
	(0.74)	(0.05)	(3.03)		(1.38)	(-0.20)	(1.57)		(1.17)	(-0.14)	(3.17)		
(3)	γ	MKT	NDU		γ	MKT	NDU		γ	MKT	NDU		
	0.37	0.22	0.03	0.68	0.34	0.16	0.04	0.53	0.36	0.20	0.03		0.64
	(0.49)	(0.26)	(2.59)		(0.31)	(0.15)	(0.92)		(0.55)	(0.27)	(3.08)		
(4)	γ	MKT	EQS		γ	MKT	EQS		γ	MKT	EQS		
	1.73	-0.99	0.80	0.67	0.92	-0.32	0.21	0.71	1.43	-0.72	0.33		0.52
	(2.12)	(-1.18)	(3.52)		(2.27)	(-0.62)	(1.51)		(3.08)	(-1.35)	(2.55)		
(5)	γ	MKT	BST		γ	MKT	BST		γ	MKT	BST		
	1.72	-0.96	0.31	0.40	0.84	-0.24	0.14	0.71	1.44	-0.74	0.18		0.44
	(2.95)	(-1.57)	(1.54)		(2.07)	(-0.47)	(1.65)		(3.12)	(-1.40)	(2.10)		
(6)									γ	MKT	RES	BST	
									0.18	0.41	0.28	0.17	0.68
									(0.28)	(0.57)	(1.97)	(2.22)	

Innovations in GDP components

The innovation of a particular state variable should carry the relevant information for stock market returns. Given that GDP components lead and lag, we reconsider our results using the innovations of GDP components derived from a VAR. Campbell (1996) and Petkova (2006) propose a similar approach.

Estimation. First, we estimate the following first-order VAR:

$$\begin{bmatrix} \Delta RES_t \\ \Delta DUR_t \\ \Delta NDU_t \\ \Delta EQS_t \\ \Delta BST_t \end{bmatrix} = \mathbf{A}_0 + \mathbf{A}_1 \begin{bmatrix} \Delta RES_{t-1} \\ \Delta DUR_{t-1} \\ \Delta NDU_{t-1} \\ \Delta EQS_{t-1} \\ \Delta BST_{t-1} \end{bmatrix} + \boldsymbol{u}_t,$$

where $\boldsymbol{u}_t$ represents a vector of five innovations in GDP components. Second, we construct five mimicking portfolios for each element of $\boldsymbol{u}_t$, as is in the main paper for the simple growth rates. An alternative to the VAR approach would be to include lagged GDP components on the right hand side when estimating GDP mimicking portfolio factors, as in Lamont (2001) or Vassalou (2003). In unreported tests we find that this alternative procedure leads to very similar results as the VAR innovations.

Results. Table OA.8 shows cross-sectional regression results for mimicking portfolio factors of GDP component VAR innovations. Overall, we find only little difference to the results based on parsimonious growth rates provided in the main text.

Table OA.8: Innovations in GDP Components

The table reports GMM estimates of a constant (γ) and factor prices (λ) as in the main paper, except that we use monthly GDP mimicking portfolios based on the innovations of a VAR system containing the five GDP components. T-statistics are reported in parentheses and are based on the Newey and West (1987) HAC covariance matrix with automatic lag length selection according to Andrews (1991). The sample period is from January 1951 to December 2010.

	γ	Factor Price (λ)		R^{2OLS}	γ	Factor Price (λ)		R^{2OLS}	γ	Factor Price (λ)			R^{2OLS}
	FF25				Momentum 10				FF25 + M10				
(1)	γ	MKT	RES		γ	MKT	RES		γ	MKT	RES		
	0.50	0.12	0.98	0.83	0.17	0.42	1.31	0.88	0.37	0.23	1.12		0.87
	(1.13)	(0.24)	(2.64)		(0.49)	(1.12)	(3.25)		(0.92)	(0.50)	(3.46)		
(2)	γ	MKT	DUR		γ	MKT	DUR		γ	MKT	DUR		
	0.67	0.12	1.97	0.58	0.23	0.41	1.55	0.90	0.52	0.22	1.67		0.71
	(1.39)	(0.22)	(4.92)		(0.64)	(1.03)	(3.54)		(1.24)	(0.47)	(4.27)		
(3)	γ	MKT	NDU		γ	MKT	NDU		γ	MKT	NDU		
	-0.42	1.08	1.21	0.51	-0.22	0.80	1.18	0.88	-0.51	1.14	1.32		0.71
	(-0.83)	(1.88)	(3.08)		(-0.52)	(1.83)	(3.49)		(-1.03)	(2.12)	(4.40)		
(4)	γ	MKT	EQS		γ	MKT	EQS		γ	MKT	EQS		
	1.43	-0.61	1.11	0.16	0.61	0.05	1.62	0.91	1.21	-0.42	1.73		0.48
	(4.04)	(-1.47)	(2.35)		(1.87)	(0.14)	(3.57)		(3.54)	(-1.06)	(4.05)		
(5)	γ	MKT	BST		γ	MKT	BST		γ	MKT	BST		
	0.31	0.37	1.66	0.32	0.35	0.27	1.14	0.90	0.44	0.25	1.28		0.64
	(0.68)	(0.70)	(2.62)		(1.17)	(0.75)	(3.46)		(1.19)	(0.61)	(4.82)		
(6)									γ	MKT	RES	BST	
									0.34	0.27	1.10	0.98	0.87
									(0.82)	(0.61)	(3.41)	(3.45)	

Quarterly GDP Data

We rely on annual GDP data in the main text. GDP estimates are also available at the quarterly frequency. However, there are several reasons to suspect that quarterly GDP data are more prone to measurement error than annual data - a fact which is often overlooked.

Intra-year estimates of GDP are based on less comprehensive monthly surveys. If no monthly survey is available, interpolation and other methods are used for intra-year estimates. Furthermore, intra-year estimates are subject to seasonality and thus seasonal adjustments which come naturally in different shades for the different GDP components (see e.g., Ferson and Harvey (1992) for a discussion of the seasonality issue and the impact of adjustments). For example, residential investment is more prone to seasonality than investment in equipment and software.

Estimation. To reduce these potential problems, we apply a two quarters moving average for all five GDP components at the quarterly frequency:

$$\Delta\tilde{Y}_{j,t} = \frac{Y_{j,t} + Y_{j,t-1}}{Y_{j,t-1} + Y_{j,t-2}} - 1.$$

This averaging adjustment is also used by Jagannathan and Wang (1996) for labor income growth as a risk factor. Following, we calculate GDP mimicking portfolio weights based on $\Delta\tilde{Y}_{j,t}$ and use these weights with monthly stock market data.

Results. Table OA.9 shows results for the GDP mimicking portfolio factors based on quarterly data. Overall, the mimicking portfolio weights and factor loadings are very similar as in the main text. Leading GDP components load on HML, lagging GDP components load on WML.

One exception is observed for DUR. Using quarterly data, the weights on the mid/big and high/big portfolio are extreme, resulting in a large monthly standard deviation of 10.2%. In Table OA.10 we find similar cross-sectional results for the monthly GDP mimicking portfolios based on quarterly GDP data as we find for monthly GDP mimicking portfolios based on annual GDP data in the main text. Only results for the DUR factor (specification 2) are considerably inferior.

Table OA.9: GDP Mimicking Portfolios Based on Quarterly Data

Panel A reports estimates of $j = 1, ..., 6$ mimicking portfolio weights for aggregate GDP (GDP), residential investment (RES), durables (DUR), nondurables (NDU), equipment and software (EQS) and business structures (BST). We regress the real per capita growth rate of quarterly aggregate GDP and each of the quarterly GDP components ($\triangle\tilde{Y}_{j,t}$) on six annual Fama-French portfolios, $FF6_t$, sorted by size and book-to-market (low/small, mid/small, high/small, low/big, mid/big, high/big) and the momentum factor, WML_t:

$$\triangle\tilde{Y}_{j,t} = a_j + \mathbf{p}_j' \left[\mathbf{FF6}_t',\ WML_t\right]' + \epsilon_{j,t}.$$

The resulting weights $\hat{\mathbf{p}}_j$ are normalized, such that their sum is one: $\hat{\mathbf{w}}_j = \hat{\mathbf{p}}_j \left(\mathbf{1}'\hat{\mathbf{p}}_{,j}\right)^{-1}$. Monthly GDP mimicking portfolios are calculated as: $MPm_{j,t} = \hat{\mathbf{w}}_j' \left[\mathbf{FF6m}_t',\ WMLm_t\right]'$, where $\mathbf{FF6m}_t$, and $WMLm_t$ are monthly measured returns of the six Fama-French portfolios and the momentum factor. Panel B reports the mean (%), standard deviation (%), Sharpe ratio and the factor exposures (betas) of the six monthly GDP mimicking portfolios:

$$MPm_{j,t} = \alpha_j + \beta_{MKT,j}MKT_t + \beta_{SMB,j}SMB_t + \beta_{HML,j}HML_t + \beta_{WML,j}WML_t,$$

where MKT is the market excess return, SMB is the small minus big factor, HML is the high minus low factor, and WML is the winner minus loser (momentum) factor. The sample period is from January 1951 to December 2010.

	GDP	RES	DUR	NDU	EQS	BST
Panel A:	Normalized GDP mimicking portfolio weights					
low/small	-0.76	-0.74	-2.11	-0.24	-1.02	0.38
mid/small	0.23	0.54	-0.26	0.40	-2.86	-0.30
high/small	0.42	0.53	2.24	-0.24	3.16	-1.62
low/big	0.42	0.27	1.35	-0.26	0.42	-0.57
mid/big	-1.07	-0.49	-4.22	-0.36	0.39	-0.75
high/big	1.07	0.40	3.43	1.07	-0.20	2.46
momentum	0.69	0.50	0.58	0.63	1.11	1.40
Panel B:	Statistics of monthly mimicking portfolio factors					
Mean (%)	1.13	1.15	2.14	0.91	1.32	0.42
SD (%)	3.84	3.14	10.24	3.24	7.02	7.37
Sharpe ratio	0.30	0.37	0.21	0.28	0.19	0.06
α	0.00	0.00	0.00	-0.00	0.00	-0.00
s.e.	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
β_{MKT}	0.35	0.47	0.63	0.41	-0.07	-0.19
s.e.	(0.02)	(0.01)	(0.09)	(0.01)	(0.04)	(0.04)
β_{SMB}	-0.15	0.15	-0.08	-0.04	-0.74	-1.06
s.e.	(0.03)	(0.02)	(0.13)	(0.02)	(0.05)	(0.06)
β_{HML}	0.93	0.82	2.94	0.81	1.33	0.46
s.e.	(0.03)	(0.02)	(0.14)	(0.02)	(0.07)	(0.06)
β_{WML}	0.69	0.51	0.59	0.61	1.15	1.34
s.e.	(0.03)	(0.02)	(0.09)	(0.01)	(0.04)	(0.04)

Table OA.10: GDP Mimicking Portfolio Factors Based on Quarterly Data

The table reports GMM estimates of a constant (γ) and factor prices ($\boldsymbol{\lambda}$) as in the main paper, except that we use monthly GDP mimicking portfolios based on quarterly GDP data. T-statistics are reported in parentheses and are based on the Newey and West (1987) HAC covariance matrix with automatic lag length selection according to Andrews (1991). The sample period is from January 1951 to December 2010.

	γ	Factor Price ($\boldsymbol{\lambda}$)		R^{2OLS}	γ	Factor Price ($\boldsymbol{\lambda}$)		R^{2OLS}	γ	Factor Price ($\boldsymbol{\lambda}$)			R^{2OLS}
	FF25				Momentum 10				FF25 + M10				
(1)	γ	MKT	RES		γ	MKT	RES		γ	MKT	RES		
	0.19	0.41	0.98	0.74	0.12	0.46	1.08	0.88	0.14	0.45	1.04		0.84
	(0.42)	(0.79)	(2.75)		(0.37)	(1.26)	(3.59)		(0.34)	(0.99)	(3.87)		
(2)	γ	MKT	DUR		γ	MKT	DUR		γ	MKT	DUR		
	0.49	0.21	1.87	0.44	-1.36	1.74	15.96	0.41	0.63	0.02	2.03		0.29
	(1.16)	(0.43)	(3.08)		(-0.58)	(0.84)	(1.05)		(1.70)	(0.06)	(3.26)		
(3)	γ	MKT	NDU		γ	MKT	NDU		γ	MKT	NDU		
	0.40	0.29	0.80	0.33	0.21	0.39	0.96	0.88	0.16	0.49	1.01		0.65
	(0.98)	(0.62)	(2.25)		(0.66)	(1.09)	(3.81)		(0.43)	(1.15)	(4.33)		
(4)	γ	MKT	EQS		γ	MKT	EQS		γ	MKT	EQS		
	1.07	-0.27	0.49	0.14	-0.09	0.71	1.73	0.86	0.07	0.68	1.28		0.37
	(3.72)	(-0.86)	(1.00)		(-0.20)	(1.47)	(3.61)		(0.16)	(1.44)	(3.99)		
(5)	γ	MKT	BST		γ	MKT	BST		γ	MKT	BST		
	2.15	-1.49	-1.18	0.61	0.31	0.33	1.50	0.89	1.06	-0.30	0.76		0.17
	(4.64)	(-3.17)	(-1.80)		(0.95)	(0.86)	(3.45)		(3.03)	(-0.77)	(2.23)		
(6)									γ	MKT	RES	BST	
									0.19	0.39	1.01	0.72	0.84
									(0.47)	(0.89)	(3.86)	(2.02)	