Creative Destruction and Asset Prices

Joachim Grammig and Stephan Jank*

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Keywords: creative destruction, asset pricing, size and value premium, patents, HML, SMB

JEL: G10, G12

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This paper introduces Schumpeter's idea of creative destruction into asset pricing. The key point of our model is that small-value firms are more likely to be destroyed during technological revolutions, while large-growth firms provide a hedge against creative destruction risk. The expected return difference between assets with the highest and lowest exposure to creative destruction risk amounts to 8.6 percent annually. A model including market return and invention growth as priced factors accounts for a large portion of the cross-sectional variation of size and book-to-market sorted portfolios and successfully prices HML and SMB.

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Historically, small stocks have outperformed large stocks and value stocks have outperformed growth stocks. These size and value premia are insufficiently explained by the Capital Asset Pricing Model (CAPM). While the Fama-French three-factor model is able to account for the size and value premia, it leaves the question of what the fundamental risk is behind HML and SMB unanswered.

This paper introduces Schumpeter's idea of creative destruction into asset pricing theory as an explanation for the size and value premia. The idea is that new and better products can render existing ones obsolete, posing an imminent risk for any investment made. This "process of industrial mutation [...] that incessantly revolutionizes the economic structure *from within*, incessantly destroying the old one, incessantly creating a new one" (Schumpeter 1961, p. 83) can be seen throughout history. Means of transportation, for example, developed within a century from horse carriage to railroad, automobile and airplane, each invention challenging the previous. Looking at the most recent technological revolution in the 1990s, inventions in the field of software and information technology led, on the one hand, to increased productivity and economic growth; on the other hand, they challenged existing business models of the music industry, media and printed newspapers. Thus, in the sense that inventions are the ultimate driver of economic growth, inventions are also the ultimate risk for an investment - namely the risk that the business idea becomes obsolete.

We propose an asset pricing model with creative destruction risk in which small and value stocks incur a higher probability of becoming destroyed during times of technological change. Previous work shows that companies with a low market value and a high book-to-market ratio are firms under distress: they are less productive and have a higher probability of default (c.f. Chan & Chen 1991, Fama & French

1995, Vassalou & Xing 2004). These distressed firms are less likely to survive technological revolutions. In equilibrium, investors have to be compensated for the risk of creative destruction, resulting in higher expected returns for small and value stocks.

Our model is a two-factor model in the spirit of Merton's (1973) Intertemporal Capital Asset Pricing Model (ICAPM). It includes market return and innovation growth, proxied by the change in patent activity as state variables. An increase of invention activity raises the risk of creative destruction and thus reduces expected cash flows of existing businesses. Long-horizon investors will prefer assets that are less exposed to creative destruction as they provide a hedge against reinvestment risk.

We find that returns of small and value stocks are negatively related to invention growth, which results in an economically significant risk premium. Small value stocks have the highest exposure to creative destruction risk and offer an additional 6.2 percent expected excess return per year. Large growth stocks, on the contrary, provide a hedge against creative destruction, resulting in a discount of expected excess return of 2.4 percent annually. The creative destruction risk model does a good job in pricing the 25 size and book-to-market sorted portfolios with the exception of the small-growth portfolio. The model is not rejected by the GMM J-test and achieves a cross-sectional R^2 of 60 percent. Finally, a patent activity growth-mimicking portfolio can price both HML and SMB, suggesting that invention growth is the real economy state variable captured by the Fama-French factors.

Our study connects several strands of literature. It relates the idea of creative destruction - an idea well established in the Schumpeterian growth theory (e.g. Segerstrom et al. 1990, Grossman & Helpman 1991, Aghion & Howitt 1992, Helpman & Trajtenberg 1994) - to asset pricing. In this way we contribute to a growing body of literature that investigates the effects of technological innovations on asset prices (Nicholas 2008, Comin, Gertler & Santacreu 2009, Hsu 2009, Pástor & Veronesi 2009). Furthermore, we incorporate creative destruction risk into Merton's (1973) ICAPM, arguing that investment opportunities change because new technologies render existing businesses obsolete. This links our contribution to others that have empirically tested the ICAPM (e.g. Campbell 1993, 1996, Campbell & Vuolteenaho 2004, Brennan et al. 2004).

Moreover, our work complements the literature that attempts to explain the size and value puzzle. In particular, it refers to papers that associate market value and book-to-market ratio with measures of firm distress (e.g. Chan et al. 1985, Chan & Chen 1991, Fama & French 1995). While this literature links size and book-to-market ratio to distress of *individual* firms, a connection to an *aggregate* distress factor has not been established (Lakonishok et al. 1994, Vassalou & Xing 2004). But to obtain a premium for size and value, we require a macro distress factor because idiosyncratic distress risk can be diversified away (Cochrane 2008). Our model links the individual firm's default risk to the macro variable patent activity, the proxy for creative destruction risk.

1 A Simple Model of Creative Destruction and Asset Prices

1.1 Technological Change and Asset Payoffs

This section presents a simple model of creative destruction that explains why small and value firms face a higher risk of being destroyed during times of technological change. The model embodies the notion that individual inventions have the potential to affect the whole economy (Aghion & Howitt 1992, Bresnahan & Trajtenberg 1995), and thus present a fundamental risk factor for investors. Examples of such pervasive inventions are the steam engine, the electric motor and the semi-conductor. Due to their impact on a wide range of sectors, Helpman & Trajtenberg (1994) refer to these inventions as "general purpose technologies". General purpose technologies foster productivity gains and economic growth, but they also render older technologies obsolete and destroy existing businesses. Our model explains how investors take this ambivalent nature of inventions into account, and derives implications for asset prices.

The business model of firm i generates the payoff $X_{i,t+1}$. N_t inventions occur in period t, each of which can destroy firm i with probability π_i. If π_i is small and N_t large, the number of inventions $D_{i,t+1}$ that destroy firm i follows a Poisson distribution with $\lambda_{i,t} = \pi_i \cdot N_t$. In the event that the business is destroyed ($D_{i,t+1} > 0$), the payoff $X_{i,t+1}$ equals zero. Thus, we can write the expected payoff at time t in the following way:

$$\mathbb{E}_t[X_{i,t+1}] = \exp(-N_t \cdot \pi_i)\, \mathbb{E}_t[X_{i,t+1}|D_{i,t+1} = 0], \qquad (1)$$

where $P(D_{i,t+1} = 0) = \exp(-N_t \cdot \pi_i)$ gives the probability that firm i survives. The number of inventions N_t is a state variable, which influences the conditional distribution of $X_{i,t+1}$. Since more innovations have the chance of destroying the business, the expected payoff decreases when the number of inventions rises, as can be seen from

$$\frac{\partial \mathbb{E}_t[X_{i,t+1}]}{\partial N_t} = -\pi_i \cdot \exp(-N_t \cdot \pi_i)\, \mathbb{E}_t[X_{i,t+1}|D_{i,t+1} = 0] < 0. \qquad (2)$$

The negative effect of an increase in inventions on the conditional expected payoff is stronger for firms with a higher individual baseline probability π_i as long as the probability that the firm survives is sufficiently high.[1] Firms with a high π_i are more exposed to the risk of destruction induced by an increase in inventions N_t.

What are the characteristics of firms with a high baseline probability of default? Vassalou & Xing (2004) provide evidence of higher default risk for value stocks. Fama & French (1995) find that value stocks are less profitable than growth stocks four years before and five years after their ranking. That small firms possess a higher default risk is shown by Chan et al. (1985) and Vassalou & Xing (2004). Furthermore, Chan & Chen (1991) find that small firms contain a large proportion of marginal firms, i.e. firms with low production efficiency. Inefficient firms may not survive times of technological change and thus face a high default risk. In summary, the previous literature identifies small and value firms as being distressed, i.e. as high π-firms.

Relating these findings to our model, it follows that the negative impact of an increase in inventions on expected payoffs should be stronger for small and value stocks. Thus, the model establishes the link between the *individual* destruction probability π_i and the *aggregate* risk factor inventions, N_t. Investors who hold stocks which are more exposed to creative destruction risk have to be compensated by higher expected returns in equilibrium.

[1] Differentiating (2) with respect to π_i gives

$$\frac{\partial^2 \mathbb{E}_t[X_{i,t+1}]}{\partial N_t \partial \pi_i} = (\pi_i N_t - 1) \cdot \exp(-N_t \cdot \pi_i)\, \mathbb{E}_t[X_{i,t+1} | D_{i,t+1} = 0].$$

This expression is negative for $\lambda_{i,t} = \pi_i \cdot N_t = \mathbb{E}[D_{i,t+1}] < 1$, i.e. if the expected number of innovations that destroy the firm is less or equal to one. This corresponds to a survival probability of at least $P(D_{i,t+1} = 0) = \exp(-1) = 0.37$.

1.2 The Household's Intertemporal Optimization Problem

We now outline an equilibrium model that accounts for the risk of creative destruction. The result is a two-factor model including changes in wealth and invention growth as state variables. It is a special case of Merton's (1973) ICAPM in discrete time.

In an infinite-period setting, a representative investor maximizes his or her expected life-time utility of consumption:

$$U = \mathbb{E}_t \sum_{j=0}^{\infty} \delta^j u(c_{t+j}), \tag{3}$$

where c_t is consumption and δ the subjective discount rate. The investor can buy a portfolio of n assets that generates wealth $W_{t+1} = R^W_{t+1}(W_t - c_t)$, where $R^W_{t+1} = \sum_{i=1}^{n} w_i R_i$ with portfolio weights w_i totaling one. Fama (1970) shows that the infinite-period problem can be expressed as a two-period problem with

$$U = u(c_t) + \delta \mathbb{E}_t[V(W_{t+1}, N_{t+1})], \tag{4}$$

where the value function $V(\cdot)$ is defined as the maximized value of the utility function, which depends on observable state variables that account for shifts in the investment opportunity set. In our case, the value function depends on the investor's wealth W_{t+1} and the number of inventions N_{t+1}. The number of inventions captures the risk of creative destruction and the changes in investment opportunities induced by them. In a state of the world where many inventions occur - a technological revolution - it is riskier to invest in firms which are already under distress and thus might not survive. This has to be accounted for in the investor's optimization problem.

The first-order condition for optimal consumption and portfolio choice is given by

$$p_{i,t}u'(c_t) = \delta \mathbb{E}_t[V_W(W_{t+1}, N_{t+1})X_{i,t+1}], \tag{5}$$

where $p_{i,t}$ is the price of asset i, $X_{i,t+1}$ its payoff and $V_W(\cdot)$ refers to the derivative of the value function with respect to wealth W. Using the envelope condition $u'(c_t) = V_W(W_t, N_t)$, the stochastic discount factor can be written as

$$M_{t+1} = \delta \frac{V_W(W_{t+1}, N_{t+1})}{V_W(W_t, N_t)}. \tag{6}$$

First-order Taylor approximation yields the following linearized stochastic discount factor:

$$M_{t+1} = a_t + b_{1,t}\frac{W_{t+1}}{W_t} + b_{2,t}\frac{N_{t+1}}{N_t}. \tag{7}$$

Equation (5) implies the fundamental pricing equation for excess returns:

$$\mathbb{E}_t[M_{t+1}R^e_{i,t}] = 0. \tag{8}$$

The corresponding expected return-beta representation reads:

$$\mathbb{E}_t[R^e_{i,t+1}] = \beta_{W,t}\lambda_{W,t} + \beta_{N,t}\lambda_{N,t}, \tag{9}$$

where $\lambda_{W,t}$ and $\lambda_{N,t}$ capture the price of market and creative destruction risk, and $\beta_{W,t}$ and $\beta_{N,t}$ are projection coefficients which measure the asset-specific exposure to these risks.

We refer to this ICAPM with the two factors wealth portfolio and invention growth as Creative Destruction Risk (CDR) model. Note that in the case of no changes in the investment opportunity set, i.e. if the value function only depends on wealth $V(W_{t+1})$, the expected excess return of an asset is solely determined by its exposure to market risk. The model simplifies to the CAPM. But investment opportunities do change: inventions make certain businesses obsolete and create new investment opportunities. The factor invention growth, N_{t+1}/N_t, captures this change in investment opportunities. Equation (9) shows that an investor needs to be compensated by a higher expected return when holding assets which are more exposed to the risk of creative destruction.

2 Data

The key state variable in our model is invention activity. Equation (7) states that changes in the investment opportunity set are related to invention growth, which we approximate by the percentage change of patents issued, patent activity growth (PAG). Data on newly issued patents come from the master classification file of the United States Patent and Trademark Office (USPTO).

We argue that creative destruction risk is indeed best measured by overall patent activity growth. Of course, in hindsight some patents prove to be more relevant than others. Accounting for this difference using subsequent patent citations is an important issue when measuring the technological impact of a specific invention (Nicholas 2008). This issue loses relevance, however, when measuring creative destruction risk. *Ex-post* we *observe* the success or failure of an invention, and its creative destruction effects. But we are interested in the *probability* that an invention will destroy businesses. This is the risk that an investor faces *ex-ante*. We argue above that any patent has the potential to make an existing business obsolete. The example of laser technology, which revolutionized medicine, warfare, and telecommunications alike, shows the serendipitous effect of an innovation that was unforeseeable ex-ante (Townes 2003). It is thus the overall number of patents that best captures the risk of creative destruction.

In our main analysis we use annual data on the 25 size and book-to-market sorted portfolios ranging from 1927-2008. Data on portfolio returns and Fama-French factors are obtained from Kenneth French's homepage. We consider the longest possible sample, starting in 1927, the first available year of size and book-to-market sorted portfolios. We choose a long-run, low frequency perspective for the following reasons. First, the proxy patent activity may be prone to measurement error. The number of patents issued in a certain period can be influenced by other factors, such as institutional settings of the patent office or backlogs in the patent issuing process. These effects are presumably aggravated at higher frequencies. Furthermore, annual patent activity is arguably more suitable for capturing technological waves, which generally range over many years. The long-run perspective also complies with the ICAPM framework, in which an investor maximizes life-time utility.

[Insert Table 1 and Figure 1 about here]

Table 1 contains descriptive statistics on patent activity growth, market excess return and the Fama-French factors. Figure 1 depicts time-series of HML, SMB and patent activity growth. We use the value-weighted NYSE, AMEX and NASDAQ stocks as a proxy for the wealth portfolio. The market excess return (MKT) is the return of this portfolio minus the one-month Treasury Bill rate. The mean market excess return in our sample is 7.6 percent annually, which can be interpreted as the equity premium. HML (High Minus Low) is a portfolio that has long positions in stocks with high book-to-market value and short positions in stocks with low book-to-market value. Similarly, SMB (Small Minus Big) is a portfolio long in small stocks and short in large stocks.[2] The average premium associated with a size and value investment strategy is 3.6 percent for SMB and 5.1 percent for HML, respectively.

[Insert Table 2 about here]

The size and value premia are also apparent from Table 2, which shows the average excess returns and standard deviations of the 25 portfolios sorted by size and book-to-market. Excess returns are computed by subtracting the one-month T-Bill rate from the raw returns. Going from left to right, value firms earn less than growth firms, and, moving from top to bottom, small firms earn more than large firms. The small-growth portfolio with an average annual excess return of just 3.7 percent is a well-known exception.

Patent activity growth averages at 2.4 percent and is considerably volatile, with a standard deviation that is comparable to HML and SMB. The PAG series shows no sign of autocorrelation and thus qualifies as a variable that captures unexpected news with regard to technological change. An important empirical finding, which we will elaborate on below, is that the macro variable patent activity growth is negatively correlated with both HML and SMB portfolio returns.

3 Estimation Results and Discussion

3.1 Exposure to Creative Destruction Risk

Using the 25 test portfolios mentioned above, we estimate the creative destruction risk model by means of two-pass regressions and GMM, exploiting the unconditional

[2] For details on the construction of the portfolios, see Fama & French (1993).

moment restrictions implied by equation (8). Conditioning down and assuming time invariant parameters in (7), estimates of the market- and PAG-beta can be obtained by time-series regressions of excess returns on factors:

$$R^e_{i,t} = a_i + \beta_{MKT,i} MKT_t + \beta_{PAG,i} PAG_t + \varepsilon_{i,t}. \tag{10}$$

Factor risk premia λ_{MKT} and λ_{PAG} are estimated by a cross-sectional regression of average excess returns on beta estimates obtained in the first step. To calculate standard errors, we use the Shanken (1992) correction.

[Insert Table 3 about here]

Table 3 displays the result of the time-series regression in Panel A. Here we report the estimates of the market beta, the patent activity growth beta and the R^2 of each time-series regression; Panel B shows the estimated factor risk premia $\hat{\lambda}_{MKT}$ and $\hat{\lambda}_{PAG}$.

The beta estimates vary considerably across portfolios with different size and book-to-market value, with a pattern that is consistent with the theoretical model of creative destruction risk. Small value firms have the strongest negative exposure to patent activity growth, with the estimate $\hat{\beta}_{PAG}$ equal to -0.42 and a t-statistic of -2.3. Our theoretical framework suggests that these stocks possess a high baseline destruction probability π_i. A technology shock hits these firms' expected payoffs the hardest, resulting in a large drop in their prices, which corresponds to a pronounced negative beta loading.

Large growth firms, in contrast, have positive exposure to patent activity growth; the coefficient estimate $\hat{\beta}_{PAG}$ equals 0.16, while the t-statistic is 2.8. These stocks can generally be characterized by strong earnings growth and high profitability ratios and thus are most likely to persist throughout the technological revolution. Relatively speaking, large growth stocks might even profit from the weakness of their competitors and gain market power. This fact results in a positive beta loading with patent activity growth.

[Insert Table 4 about here]

Creative destruction entails a considerable risk that is priced by the stock market. Panel B in Table 3 provides the $\hat{\lambda}$ estimates, which amount to 7.0 percent for the market factor and -14.6 percent for patent activity growth, significant from both a statistical and an economic point of view. Table 4 displays the estimated premia attributed to market risk $\hat{\lambda}_{MKT} \cdot \hat{\beta}_{MKT}$ and to creative destruction risk $\hat{\lambda}_{PAG} \cdot \hat{\beta}_{PAG}$, respectively. When we look at risk premium associated with creative destruction, small value firms earn an additional expected excess return of 6.2 percent annually due to their high risk of becoming obsolete during times of technological change. The opposite is the case for large growth firms, whose positive loading with patent activity growth leads to a discount in expected excess returns of 2.4 percent. Overall, this yields a spread in expected excess returns of 8.6 percentage points between assets with the highest and assets with the lowest exposure to creative destruction risk.

3.2 Model Comparison

We now compare the empirical performance of the Creative Destruction Risk (CDR) model to the CAPM (Sharpe 1964, Lintner 1965, Mossin 1966) and the Fama-French (1995) three-factor model. The CAPM can be seen as a special case of the CDR model in which investment opportunities do not change. The Fama-French model with the SMB and HML factors represents the natural benchmark for the 25 size and book-to-market sorted portfolios. The purpose of this section is not to run a horse race between the portfolio-based Fama-French model and our macro factor model. As pointed out by Cochrane (2008), portfolio-based models will have a head start on the 25 portfolios, which exhibit a correlation structure that is well captured by three principal components (see also Lewellen, Nagel & Shanken 2010). The CAPM and the Fama-French model rather serve as upper and lower benchmarks to gauge the ability of the CDR model to account for size and value premia.

GMM estimation based on the stochastic discount factor representation (8) provides a convenient framework for model comparisons. The stochastic discount factors M_{t+1} for CAPM, Fama-French model and CDR model are given by

$$
\begin{aligned}
&b_0 + b_{MKT} MKT_{t+1} && \text{(CAPM)} \\
&b_0 + b_{MKT} MKT_{t+1} + b_{HML} HML_{t+1} + b_{SMB} SMB_{t+1} && \text{(Fama-French model)} \\
&b_0 + b_{MKT} MKT_{t+1} + b_{PAG} PAG_{t+1} && \text{(CDR model).}
\end{aligned}
$$

Since we use excess returns as test assets, we de-mean all factors and set $b_0 = 1$ to ensure identification.

We report first-stage GMM estimates, with the identity matrix as a pre-specified weighting matrix, and second-stage GMM estimates using an estimate of the optimal weighting matrix. Our analysis focuses on first-stage GMM results. By giving every portfolio the same weight, the model is forced to explain the size and value premium (Cochrane 2005). Second-stage GMM provides more efficient estimates, but often prices rather unusual long-short combinations of portfolios, and does not allow a comparison across models (Parker & Julliard 2005). We consider second-stage GMM results as a robustness check for our results. Following Jagannathan &

Wang (1996), we report the cross-sectional R^2 as an informal and intuitive measure of goodness-of-fit.[3]

[Insert Table 5 about here]

Table 5 contains first- and second-stage GMM results. Estimation of the CAPM and Fama-French model delivers the familiar results. The market excess return is a relevant pricing factor, but taken alone fails to explain the size and value premia. The R^2 is low at 26 percent, and the GMM J-test rejects the CAPM on conventional significance levels. Including SMB and HML in the stochastic discount factor, the Fama-French model performs better, although SMB is not statistically significant in this sample. The R^2 amounts to 81 percent. Nevertheless, the J-test rejects the Fama-French model on the five percent level. Second-stage coefficient estimates for both models are similar to the first-stage results.

For the CDR model we find a significant market factor with a coefficient estimate comparable in size to the Fama-French model, and a highly significant coefficient for patent activity growth. The CDR model cannot be rejected on conventional significance levels by the first-stage GMM J-test. Second-stage GMM yields qualitatively similar results. In terms of goodness of fit, the CDR model shows a clear improvement compared to the CAPM, with an R^2 of 60 percent.

For a more detailed performance evaluation, Figure 2 plots average realized excess returns vs. fitted expected excess returns for the CAPM, Fama-French and CDR models. A good model fit is indicated if portfolios align along the 45-degree line. Each of the 25 test assets is numbered; the first digit refers to the size quintile

[3]To calculate the R^2 we run a cross-sectional regression of average realized excess returns on betas *including* a constant, since only in this case is the decomposition in explained and residual variation sensible. See Cochrane (2008) for further discussion.

and the second digit to the book-to-market quintile. For example, 15 refers to the portfolio with the smallest market value and the highest book-to-market ratio.

[Insert Figure 2 about here]

The first graph of Figure 2 depicts the well-known deficiency of the CAPM in accounting for cross-sectional return differences of size and book-to-market sorted portfolios. Unsurprisingly, the Fama-French model is more successful in pricing these portfolios. The CDR model, which includes patent activity growth in addition to the market factor, considerably improves the empirical performance as well. The model is particularly effective in pricing the small value portfolios 14 and 15. Our model of creative destruction implies that small and value firms are those with the highest risk of becoming obsolete. The additional risk premium for creative destruction thus corrects the mispricing of the CAPM.

While the CDR model generally improves the pricing of the 25 test assets, it fails to account for the small return of portfolio 11. The small-growth portfolio is well-known to present a challenge to asset pricing models (c.f. Yogo 2006, Campbell & Vuolteenaho 2004). Figure 2 shows that this also holds true for the Fama-French model. D'Avolio (2002), Mitchell et al. (2002) and Lamont & Thaler (2003) document limits to arbitrage due to short-sale constraints for small-growth stocks, which offers an explanation for the difficulty to price the small-growth portfolio. The limits of arbitrage argument is also consistent with our findings from the time-series regression. Table 3 shows a particularly low R^2 for the small-growth portfolio, indicating that this portfolio moves less with the common risk factors, which suggests the presence of market frictions.[4]

[4]The high R^2 of the Fama-French Model for all 25 portfolios in the time-series regression (c. f. Table 1, Fama & French 1996) might be a result of the inclusion of the small-growth portfolio in the construction of the SMB and HML factors.

In summary, the CDR model delivers a good performance in statistical terms and can - with the exception of the small-growth portfolio - account relatively well for the cross-sectional return differences of the 25 size and book-to-market value sorted portfolios.

3.3 A Patent Activity Growth-Mimicking Portfolio

Can patent activity growth capture the pricing information contained in the Fama-French factors? To answer this question, we adopt a factor-mimicking portfolio approach (Breeden, Gibbons & Litzenberger 1989), acknowledging that patent activity growth may be an imperfect proxy for technological change. As pointed out by Cochrane (2008), for any macro factor that prices assets we can also use its factor-mimicking portfolio. It will contain the same pricing information, it will be less prone to measurement error, and the pricing factor will be conveniently expressed in terms of portfolio returns.

To construct the PAG-mimicking portfolio, we run the following regression:

$$PAG_t = \gamma_0 + \sum_{i=1}^{K} \gamma_i R^e_{i,t} + \varepsilon_t, \tag{11}$$

where $R^e_{i,t}$ are returns in excess of the risk-free rate of K base assets. Following Vassalou (2003), we use as base assets the six portfolios formed on size and book-to-market, which are also used to construct the Fama-French factors (for details see Fama & French 1993). Using the estimated gamma-coefficients as weights, we can form the maximum correlation portfolio that mimics the patent activity growth:

$$PAGM_t = \sum_{i=1}^{K} \hat{\gamma}_i R^e_{i,t}. \tag{12}$$

Since the base assets are zero-investment portfolios, PAGM itself is a zero-investment portfolio, and we do not require the portfolio weights to add up to one.

[Insert Table 6 about here]

The estimated weights $\hat{\gamma}_i$ resulting from the time-series regression can be found in Table 6. As in Vassalou (2003), individual t-statistics are small due to multicollinear portfolio returns, but the estimated weights are jointly significant, as indicated by the F-test. While the presence of multicollinearity requires caution when interpreting the estimated weights (Lamont 2001), their pattern is still worth mentioning. The PAG-mimicking portfolio has long positions in value and large stocks and short positions in growth and small stocks, rather the opposite of the HML and SMB. The mimicking portfolio has maximum (positive) correlation with patent activity growth, and is thus essentially a hedge against creative destruction risk.

[Insert Table 7 about here]

Further properties of the PAG-mimicking portfolio are shown in Table 7. Its mean excess return is negative and statistically significant. The negative excess return is consistent with the idea that the PAG-mimicking portfolio is a hedge against the risk of creative destruction. Further, the mimicking portfolio shows a strong negative correlation with the Fama-French factors, implying that the PAG-mimicking portfolio explains a large proportion of the variation in these factors.

However, a pricing factor does not have to explain *all* variation in the Fama-French factors to be able to price assets comparably well. HML and SMB are neither derived from theory nor constructed to account for a specific economic risk. Only a part of HML and SMB may actually be relevant for the pricing of assets (Vassalou 2003, Petkova 2006).

To assess the pricing properties of the PAG-mimicking portfolio, we follow Cochrane(2008), who argues that macro models like the CDR model should focus on pricing the Fama-French factors rather than 25 highly correlated portfolios. Consequently, we run the following time-series regressions:

$$SMB_t = \alpha_S + \beta_{1,S} MKT_t + \beta_{2,S} PAGM_t + \varepsilon_{S,t} \quad (13)$$

$$HML_t = \alpha_H + \beta_{1,H} MKT_t + \beta_{2,H} PAGM_t + \varepsilon_{H,t}. \quad (14)$$

Since the right- and left-hand side variables of these equations are excess returns, testing for the significance of the estimated regression intercepts (i.e. pricing errors) is a test of whether the market factor and the PAG-mimicking portfolio can price SMB and HML. This is ultimately a test of whether the Fama-French factors contain additional information relevant for pricing assets.

[Insert Table 8 about here]

Estimation results of the regressions (13) and (14), along with restricted versions including only MKT or PAGM as regressors, are reported in Table 8. Looking at SMB results, we see that the market factor prices the SMB portfolio relatively well. The beta-coefficient on MKT is significant and the pricing error is not significantly different from zero.[5] Including PAGM in the regression, we obtain a highly significant beta estimate, the pricing error is further reduced, and the R^2 increases from 16 to 51 percent. The pricing error is actually smallest when only the PAG-mimicking portfolio is included as a regressor.

[5] The reasonable performance of the market factor in pricing the size premium is documented by e.g. Cochrane (1999).

The value puzzle is reflected in the result that the market factor alone fails to price HML. The market beta is insignificant, and the pricing error of 4.5 percent is almost as large as the average return on the HML portfolio, which equals 5.1 percent (see Table 1). Once we include the factor-mimicking portfolio, we obtain a highly significant PAGM-beta, and the adjusted R^2 increases from virtually zero to 43 percent. Most importantly, the pricing error is statistically insignificant and, with only 1.7 percent, small in economic terms.

In summary, the PAG-mimicking portfolio represents a hedge portfolio against creative destruction risk and captures well the pricing information of the Fama-French factors SMB and HML.

3.4 Technological Revolutions and the Fama-French Factors

The economic rationale behind the CDR model is that cross-sectional return differences are caused by the fact that investors want to hedge creative destruction risk. This risk changes over time, which should also be reflected in stock return movements. Figure 1 shows that positive patent activity shocks tend to be accompanied by low returns of both HML and SMB, while negative patent activity shocks coincide with high HML and SMB returns.

We observe peaks in patent activity growth in the 1950s and 1960s, as well as the late 1990s. In the 1950s and 1960s important inventions in the field of electronics, petrochemicals and aviation were made. Computer software, digital networks and information technology were revolutionized in the 1990s. Both technology waves changed the way the economy works substantially and thus brought about creative destruction. Since small and value firms possess a higher risk of becoming obsolete during technological revolutions, prices of these assets decrease. SMB and HML returns are low. Conversely, times of low risk of creative destruction, such as the 1940s or 1970s, result in high SMB and HML returns.

Looking at the technological waves of the last century it becomes clear why they presented a substantial risk to a long-horizon investor. Consider someone who was born in 1940, started to work at the age of 20, and subsequently started investing. This would have been right in the middle of the technological revolution of the 1950s and 1960s. Assuming a retiring age of 65, the investor would have started to consume savings in 2005, just after the peak of the information technology wave. At this point, the investor would still have had a life expectancy of 19 years.[6] During his or her course of life, many inventions have been made, and many businesses have been destroyed.

Technology shocks were a considerable risk for this investor in the past, and still are in the retirement years to come. Large growth firms reflect efficiency, which makes them more resilient to technological shocks, providing the investor with a hedge against creative destruction risk. Small value firms, which, due to their inefficiency, are less likely to survive technological change, expose the investor to the risk of creative destruction - a risk for which the investor demands compensation.

3.5 Robustness Checks

The results discussed in the previous sections are robust to a number of modifications. First, we confine the analysis to a post-war sample. As discussed before, our study takes a long-run, low frequency perspective in order to capture technological waves and account for the life-time horizon of the investor. The majority of empirical tests of asset pricing models, however, are conducted using post-war data

[6]Total population life expectancy in the United States, 2005. Source: National Vital Statistics Reports, Vol. 58, No. 10, March 3, 2010.

sampled at quarterly frequencies. To make our results comparable, and to show that the Great Depression and the Second World War are not the main events that drive our results, we re-run the model comparison using quarterly data from 1950:Q1-2008:Q4. Table A. I shows the results. The poor performance of the CAPM is even more severe in this period, with a cross-sectional R^2 of only 7 percent. As before, the Fama-French model achieves a high R^2 of 79 percent, but is rejected by the J-test at the 5 percent level. The results for the CDR model are confirmed: patent activity growth is a significant factor that helps to price size and book-to-market sorted portfolios, and the model is not rejected by the first-stage GMM J-test, achieving an R^2 of 56 percent, comparable in size to the long-run sample. We conclude that the Great Depression and the Second World War do not affect our findings with regard to the role of creative destruction risk in asset pricing.

Second, we also consider a slightly different set of test assets using equally weighted portfolios. Our results are also robust for this set of test assets, as can be seen from Table A. II. The CDR model is not rejected by the J-test and the R^2 is even closer to that of the Fama-French model.

Third, we acknowledge recent criticism put forth by Lewellen et al. (2010) about the widespread use of size and book-to-market sorted portfolios in empirical asset pricing. To account for the presence of strong commonalities in these portfolios, we extend our set of test assets by ten industry portfolios. Results based on this broader sample can be found in Table A. III. Again, the results are robust in terms of parameter significance, specification test, and goodness-of-fit, and confirm the conclusions drawn from the main sample.

4 Conclusion

This paper proposes a model of creative destruction and asset prices as an explanation for the size and value premia. Small and value firms have been shown to be under distress: they are less productive and have a higher default risk. These firms are less likely to survive technological revolutions, which results in higher expected returns for these stocks. An investor who maximizes life-time utility wants to hedge the reinvestment risk caused by technology shocks. Hence, patent activity growth, which reflects creative destruction risk, becomes an important state variable for the investor.

The creative destruction risk model is consistent with several findings relating to the size and value effects. It is in line with the view that HML and SMB are measures of distress (e.g. Chan et al. 1985, Chan & Chen 1991, Fama & French 1995, Vassalou & Xing 2004). Further, our results are in accordance with recent findings on the Fama-French factors by Liew & Vassalou (2000) and Vassalou (2003), who show that HML and SMB forecast GDP growth. If, as we argue, technological change is the driving force behind the Fama-French factors, it should also result in greater productivity and thus higher GDP growth in the future. The same technological change that generates growth challenges existing businesses and is thus reflected in the size and value premia.

Concluding his article on efficient markets, Fama (1991) writes: "In the end, I think we can hope for a coherent story that (1) relates the cross-section properties of expected returns to the variation of expected returns through time, and (2) relates the behavior of expected returns to the real economy in a rather detailed way" (p. 1610). This paper provides such a coherent story for the size and value effect, by explaining the variation of HML and SMB through time, and linking expected returns to a fundamental risk in the real economy: the risk of creative destruction.

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5 Tables and Figures

Table 1: Descriptive Statistics of Factors
The table reports the mean, standard deviation, first-order autocorrelation AC(1) and cross-correlations of the factors market excess return (MKT), Small Minus Big (SMB), High Minus Low (HML) and patent activity growth (PAG) (all in percent). The sample period is 1927-2008, the sampling frequency is annual, and p-values are given in parentheses.

				Correlation			
Variable	Mean	Std. Dev.	AC(1)	MKT	HML	SMB	PAG
MKT	7.6	21.0	0.04				
			(0.71)				
HML	5.1	14.0	-0.01	0.11			
			(0.90)	(0.31)			
SMB	3.6	14.4	0.28	0.41	0.08		
			(0.01)	(0.00)	(0.50)		
PAG	2.4	13.7	0.00	-0.08	-0.21	-0.21	
			(0.98)	(0.48)	(0.05)	(0.06)	

Table 2: Descriptive Statistics of Portfolio Excess Returns
The table shows summary statistics on yearly excess returns of the 25 size (vertical) and book-to-market value (horizontal) sorted portfolios from 1927-2008.

	Book-to-Market									
	Low	2	3	4	High	Low	2	3	4	High
	Mean					Standard Deviation				
Small	3.7	9.5	13.0	16.0	18.7	38.2	35.3	34.1	37.0	40.2
2	7.2	11.9	13.4	14.7	15.4	32.3	31.4	30.3	32.7	33.2
3	8.4	11.1	12.4	12.7	14.3	30.6	27.5	26.8	27.7	32.1
4	8.0	9.1	10.8	12.0	13.1	24.1	25.4	26.3	27.3	34.5
Big	7.2	7.1	8.3	8.5	10.0	21.5	19.5	22.1	25.2	31.8

Table 3: Time-Series and Cross-Sectional Regression

Panel A contains the result of the time-series regression of excess returns on factors MKT and PAG. MKT denotes the market return in excess of the risk-free rate and PAG is patent activity growth. Test assets are the 25 portfolios sorted by size (vertical) and book-to-market value (horizontal), and the sample period is 1927-2008 at annual frequency. Beta estimates for each factor are given on the left-hand side, while t-statistics adjusted for heteroscedasticity are given on the right-hand side. The table also displays the R^2 of each regression in percent. Panel B contains the risk premia (in percent) for each factor, estimated using the cross-sectional regression of average excess returns on estimated betas. We use the Shanken (1992) correction to calculate standard errors.

Panel A: Time-Series Regression

	Book-to-Market									
	Low	2	3	4	High	Low	2	3	4	High
			$\hat{\beta}_{MKT}$					$t_{\beta_{MKT}}$		
Small	1.42	1.38	1.36	1.42	1.55	11.1	13.0	14.4	12.8	13.0
2	1.32	1.31	1.24	1.31	1.33	15.3	17.0	15.7	14.6	14.5
3	1.29	1.18	1.14	1.15	1.24	17.3	19.1	18.5	17.0	12.8
4	1.06	1.09	1.14	1.12	1.37	21.5	18.9	20.0	16.1	13.6
Big	0.97	0.89	0.97	1.06	1.28	25.7	31.1	20.7	17.3	14.2
			$\hat{\beta}_{PAG}$					$t_{\beta_{PAG}}$		
Small	-0.15	-0.24	-0.30	-0.39	-0.42	-0.78	-1.47	-2.04	-2.31	-2.31
2	-0.14	-0.18	-0.26	-0.26	-0.26	-1.03	-1.54	-2.20	-1.88	-1.86
3	-0.04	-0.20	-0.18	-0.26	-0.24	-0.35	-2.11	-1.95	-2.56	-1.60
4	0.10	-0.11	-0.14	-0.23	-0.12	1.27	-1.24	-1.55	-2.19	-0.77
Big	0.16	-0.02	-0.03	-0.08	-0.11	2.82	-0.51	-0.35	-0.84	-0.79
			R^2							
Small	61.5	68.9	73.4	69.0	69.5					
2	75.2	78.9	76.6	73.9	73.4					
3	79.2	82.7	81.8	79.5	68.5					
4	85.5	82.2	83.8	77.5	70.4					
Big	89.3	92.5	84.5	79.3	72.3					

Panel B: Cross-Sectional Regression

$\hat{\lambda}_{MKT}$	7.0	$t_{\lambda_{MKT}}$	2.01
$\hat{\lambda}_{PAG}$	-14.6	$t_{\lambda_{PAG}}$	-2.06

Table 4: Expected Excess Return

The table shows estimated expected excess returns in percent that are associated with market risk $\hat{\beta}_{MKT} \cdot \hat{\lambda}_{MKT}$ and with creative destruction risk $\hat{\beta}_{PAG} \cdot \hat{\lambda}_{PAG}$. MKT denotes market excess return and PAG patent activity growth. Estimates are taken from Table 3.

	Book-to-Market				
	Low	2	3	4	High
	$\hat{\beta}_{MKT} \cdot \hat{\lambda}_{MKT}$				
Small	9.9	9.6	9.5	9.9	10.8
2	9.2	9.2	8.7	9.2	9.3
3	9.0	8.2	8.0	8.0	8.7
4	7.4	7.6	7.9	7.8	9.6
Big	6.8	6.2	6.8	7.4	8.9
	$\hat{\beta}_{PAG} \cdot \hat{\lambda}_{PAG}$				
Small	2.2	3.5	4.3	5.7	6.2
2	2.0	2.7	3.9	3.8	3.8
3	0.6	2.9	2.7	3.9	3.5
4	-1.4	1.6	2.0	3.4	1.7
Big	-2.4	0.3	0.4	1.2	1.6

Table 5: Model Comparison: CAPM, Fama-French and CDR Model

The table contains first- and second-stage GMM results of the CAPM, Fama-French and CDR models. Test assets are the 25 size and book-to-market sorted portfolios, and the sample period is 1927-2008 at annual frequency; t-values are given in parentheses. The table also reports the GMM J-statistic and associated p-value as well as the cross-sectional R^2 in percent.

	CAPM		**Fama-French Model**		**CDR Model**	
	1st Stage	2nd Stage	1st Stage	2nd Stage	1st Stage	2nd Stage
b_{MKT}	-2.02	-2.92	-1.10	-1.94	-1.18	-1.32
	(-5.46)	(-7.31)	(-1.80)	(-3.16)	(-1.88)	(-2.34)
b_{HML}			-2.76	-3.53		
			(-3.95)	(-4.63)		
b_{SMB}			-0.80	-0.17		
			(-0.20)	(0.00)		
b_{PAG}					7.54	5.24
					(3.68)	(2.74)
J-statistic	46.4	39.6	36.6	29.2	29.5	34.1
p-value	0.00	0.02	0.03	0.14	0.16	0.06
R^2	25.8		81.1		59.9	

Table 6: Weights of the PAG-Mimicking Portfolio

The table shows the results of a time-series regression $PAG_t = \gamma_0 + \sum_{i=1}^{N} \gamma_i R^e_{i,t} + \varepsilon_t$ used to estimate the weights of the PAG-mimicking portfolio. Base assets are the six portfolios sorted by size and book-to-market (small-growth, small-neutral, small-value, big-growth, big-neutral and big-value (Fama & French 1993)). The sample period is 1927-2008 at annual frequency. Coefficient estimates are reported on the left-hand side; t-values are reported on the right-hand side. The table also displays the coefficient of determination R^2 (in percent) as well as the F-statistic for the hypothesis $\gamma_1 = \gamma_2 = ... = \gamma_6 = 0$ and the corresponding p-value.

Coefficients on Base Portfolios					t-values			
	Growth	Neutral	Value	Sum		Growth	Neutral	Value
Small	0.10	-0.24	-0.09	-0.24	Small	1.18	-1.32	-0.61
Big	0.24	-0.10	0.09	0.24	Big	1.84	-0.45	0.56
Sum	0.34	-0.34	0.00		R^2		10.3	
					F-statistic		2.42	
					p-value		0.03	

Table 7: Descriptive Statistics: PAG-Mimicking Portfolio

The table provides descriptive statistics for the PAG-mimicking portfolio. It displays the mean excess return, the t-value for the null hypothesis that the average excess return is equal to zero, the portfolio's standard deviation and its correlation with the market excess return (MKT), and the Fama-French factors HML and SMB. The sample period is 1927-2008 at annual frequency.

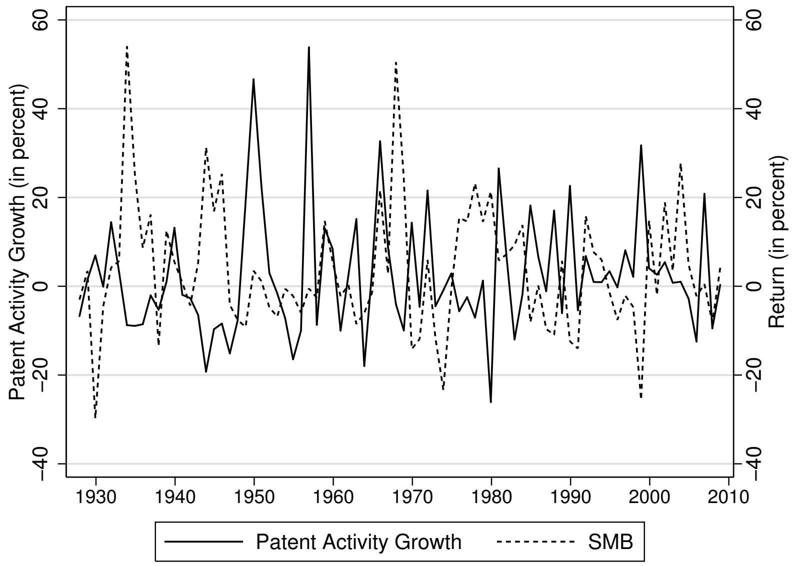
Mean		-1.66
t-value		-3.40
Std. Dev.		4.41
Correlation with:	MKT	-0.21
	HML	-0.67
	SMB	-0.66

Table 8: PAG-Mimicking Portfolio and the Fama-French Factors

The table shows the results of a time-series regression of the Fama-French factors SMB and HML on the market excess return (MKT) and the patent activity growth-mimicking portfolio (PAGM). The sample period is 1927-2008 at annual frequency. α is the intercept of the time-series regression and represents the average pricing error. The table also reports the adjusted R^2 (in percent); t-values are given in parentheses.

	SMB			HML		
MKT	0.28		0.20	0.08		-0.02
	(3.40)		(3.59)	(1.07)		(-0.31)
PAGM		-2.16	-1.96		-2.12	-2.14
		(-6.28)	(-7.53)		(-7.80)	(-7.86)
Constant: α	1.41	-0.01	-1.19	4.56	1.62	1.73
	(0.98)	(-0.01)	(-0.96)	(2.81)	(1.25)	(1.33)
Adj. R^2	16.0	43.1	50.5	0.1	43.8	43.2

(a) Patent Activity Growth and SMB



(b) Patent Activity Growth and HML

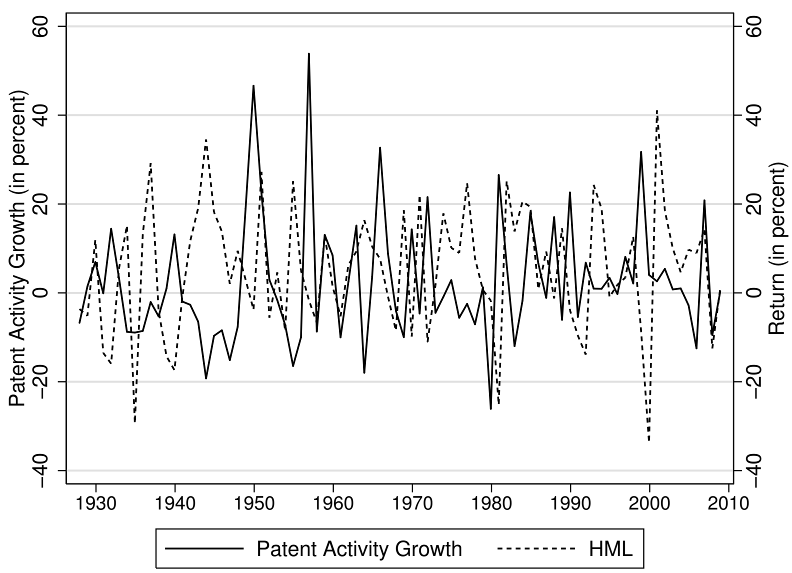
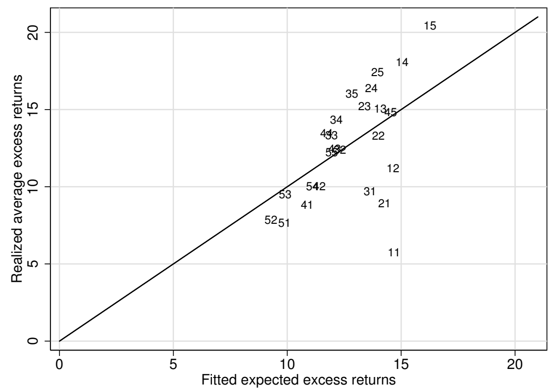
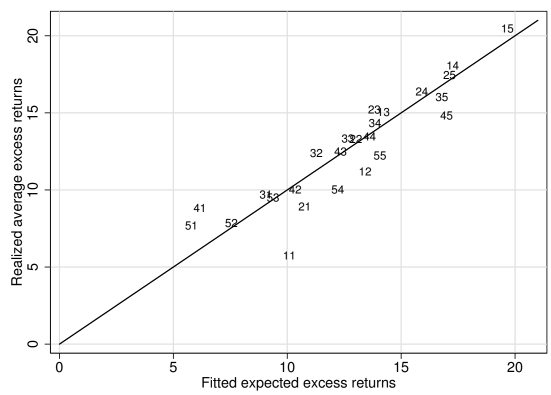


Figure 1: Patent Activity Growth and the Fama-French Factors
The graph shows patent activity growth (in percent) and the Fama-French factors Small Minus Big (SMB) and High Minus Low (HML) over the period 1927-2008.

(a) CAPM



(b) Fama-French Model



(c) CDR Model

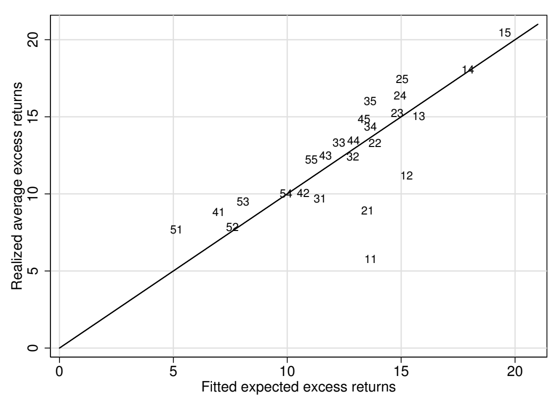


Figure 2: Fitted Expected vs. Realized Average Excess Returns
The figures compare fitted expected vs. realized average excess returns (in percent) given by the CAPM, the Fama-French model and the CDR model. The sample period is 1927-2008; the sampling frequency is annual. The test assets are the 25 portfolios sorted by size and book-to-market value, where the first number denotes the size quintile (1 being the smallest and 5 the largest), and the second number the book-to-market quintile (1 being the lowest and 5 the highest).

A Appendix

Table A. I: Model Comparison: Post-War Sample

The table contains first- and second-stage GMM results of the CAPM, Fama-French and CDR models. Test assets are the 25 size and book-to-market sorted portfolios and the sample period is 1950:Q1-2008:Q4 at quarterly frequency; t-values are given in parentheses using Newey-West standard errors with 2 lags. The table also reports the GMM J-statistic and associated p-value as well as the cross-sectional R^2 in percent.

	CAPM		**Fama-French Model**		**CDR Model**	
	1st Stage	2nd Stage	1st Stage	2nd Stage	1st Stage	2nd Stage
b_{MKT}	-3.01	-3.30	-3.78	-4.46	-1.80	-2.18
	(-3.64)	(-3.95)	(-3.74)	(-4.37)	(-1.78)	(-2.59)
b_{HML}			-6.39	-6.92		
			(-5.64)	(-6.09)		
b_{SMB}			-0.18	0.60		
			(-0.13)	(0.44)		
b_{PAG}					9.42	3.25
					(3.91)	(2.03)
J-Statistic	41.6	41.3	35.4	34.7	30.8	38.3
p-value	0.01	0.02	0.04	0.04	0.13	0.02
R^2	6.6		78.9		56.1	

Table A. II: Model Comparison: Equally-Weighted Portfolios
The table contains first- and second-stage GMM results of the CAPM, Fama-French and CDR models. Test assets are the 25 size and book-to-market sorted portfolios, equally weighted. The sample period is 1927-2008 at annual frequency; t-values are given in parentheses. The table also reports the GMM J-statistic and associated p-value as well as the cross-sectional R^2 in percent.

	CAPM		**Fama-French Model**		**CDR Model**	
	1st Stage	2nd Stage	1st Stage	2nd Stage	1st Stage	2nd Stage
b_{MKT}	-2.15	-2.71	-0.64	-1.23	-0.98	-0.79
	(-6.65)	(-7.16)	(-1.01)	(-1.90)	(-1.55)	(-1.34)
b_{HML}			-3.05	-3.72		
			(-4.58)	(-5.18)		
b_{SMB}			-1.73	-1.01		
			(-1.18)	(0.00)		
b_{PAG}					9.61	9.01
					(5.20)	(5.07)
J-Statistic	44.6	41.2	37.9	34.2	29.4	31.2
p-value	0.01	0.02	0.02	0.05	0.17	0.12
R^2	51.2		85.4		75.4	

Table A. III: Model Comparison: Extended Sample
10 Industry and 25 Size and Book-to-Market Sorted Portfolios

The table contains first- and second-stage GMM results of the CAPM, Fama-French and CDR models. Test assets are the 25 size and book-to-market sorted portfolios and 10 industry portfolios. The sample period is 1927-2008 at annual frequency; t-values are given in parentheses. The table also reports the GMM J-statistic and associated p-value as well as the cross-sectional R^2 in percent.

	CAPM		**Fama-French Model**		**CDR Model**	
	1st Stage	2nd Stage	1st Stage	2nd Stage	1st Stage	2nd Stage
b_{MKT}	-2.01	-2.88	-1.61	-2.15	-1.58	-1.48
	(-6.24)	(-8.42)	(-2.92)	(-3.95)	(-3.63)	(-3.33)
b_{HML}			-2.16	-3.01		
			(-3.32)	(-4.54)		
b_{SMB}			-0.06	0.09		
			(0.12)	(0.00)		
b_{PAG}					4.24	5.72
					(3.45)	(4.87)
J-Statistic	58.7	51.6	56.4	47.4	46.7	43.3
p-value	0.01	0.03	0.00	0.04	0.06	0.11
R^2	29.0		69.8		52.9	