EBERHARD KARLS
UNIVERSITÄT
TÜBINGEN

University of Tübingen
Working Papers in
Economics and Finance

No. 61

Creative Destruction and Asset Prices

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May 12, 2013

Abstract

We relate Schumpeter's notion of creative destruction to asset pricing, thereby offering a novel explanation of size and value premia. We argue that small-value firms are more likely to be destroyed by serendipitous invention activity, and investors demand higher expected returns for bearing that risk. Large-growth stocks provide protection against creative destruction, so they receive expected return discounts. An ICAPM that accounts for creative destruction risk explains a considerable part of the cross-sectional return variation of size- and book-to-market-sorted portfolios. The estimated risk compensations associated with creative destruction are economically and statistically significant.

Key words: creative destruction, asset prices, size premium, size premium, invention activity

JEL: G10, G12

*We thank N. Branger, W. Breuer, J. Jackwerth, H. Kraft, J.-P. Krahnen, E. Maug, R. Maurer, M. Merz, W. Pohlmeier, O. Posch, D. Rösch, M. Ruckes, S. Rünzi, E. Schaub, M. Schmeling, A. Schrimpf, W. Smith, M. Stadler, E. Theissen, G. Vilkov, U. Walz, M. Weber, as well as seminar and conference participants at U Cologne, U Frankfurt, U Groningen, U Hannover, Karlsruhe Institute of Technology, U Mannheim, U Münster, EEA/Oslo, FIRS/Sydney, U Vienna and U Warwick for helpful comments and suggestions on previous versions of this paper. We are grateful to K. French for making his financial data library publicly available, and we thank the United States Patent and Trademark Office (USPTO) for data sponsorship. Special thanks go to J. Hirabayashi (USPTO) for his exceptional support, and to J. Sönksen for research assistance. Financial support from the German Research Foundation (DFG) is gratefully acknowledged. We retain the responsibility for all remaining errors.

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1 Introduction

Small stocks have earned higher average returns than large stocks, and stocks with high book-to-market (B/M) ratio – value stocks – consistently have yielded higher average returns than growth stocks, with their low B/M ratio. These facts are insufficiently captured by empirical implementations of the static Capital Asset Pricing Model. The Fama-French three-factor model accounts for size and value premia, but it leaves the identity of the fundamental risk represented by the Fama-French factors *HML* and *SMB* uncertain.

By introducing Schumpeter's notion of creative destruction into the asset pricing literature, the present study seeks to test a novel explanation of size and value premia. Specifically, we posit that serendipitous invention activity can render business models based on current technology rapidly obsolete. This process creates a systematic risk that is reflected in sizable expected return compensations.

The "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) occurs throughout history. Means of transportation, for example, developed within a century from horse carriages to railroad, then automobiles and airplanes. Recent inventions in the field of information technology have challenged traditional business models in the music, media, and newspaper industries. Although inventions are pivotal for economic growth, they also represent a fundamental risk for existing firms and their investors, namely, the risk that their underlying business model will become obsolete.

We derive and estimate a two-factor asset pricing model in the spirit of Merton's (1973) Intertemporal Capital Asset Pricing Model (ICAPM). Our proposed model includes the wealth portfolio return and invention activity as priced factors; we refer to it as a Creative Destruction Risk Asset Pricing Model (CDRM). Using size- and

B/M-sorted portfolios as test assets, we find economically and statistically significant expected return compensations associated with the Schumpeterian risk factor *invention activity*. For the small-value portfolio, for example, we estimate that seven additional percentage points of expected return are required each year to compensate for creative destruction risk. Previous research concurs that small-value firms are under distress, in that they are less productive and have a higher default probability (c.f. Chan and Chen, 1991; Fama and French, 1995; Vassalou and Xing, 2004; Zhang, 2005). These firms therefore are less likely to weather invention-induced technological changes. An investment in large-growth stocks provides some protection against creative destruction risk, which our model reflects by estimating an expected return discount of two percentage points for the large-growth portfolio.

The empirical performance of the CDRM when we test it on size- and B/M-sorted portfolios is quite good. It achieves a cross-sectional R^2 of up to 71 percent, which is remarkably high given the model's parsimonious parametrization. Using an invention-mimicking portfolio as an alternative risk factor proxy further sharpens the results. The CDRM passes various robustness and plausibility checks. Sign and size of the estimated price of the risk associated with invention activity correspond with the invention-mimicking portfolio's mean excess return (as demanded by Lewellen et al., 2010). Furthermore, the estimated ICAPM-implied coefficient of relative risk aversion is economically plausible (≈ 1.2), as required by Maio and Santa-Clara (2012). The mimicking portfolio version of the CDRM is successful for pricing the Fama-French factors, a result consistent with the interpretation that the Fama-French factors represent creative destruction risk. For the main analysis, we adopt a long-run perspective using annual data from 1927 to 2008. The conclusions remain unchanged when we use postwar data sampled at quarterly frequency instead.

Our study connects several strands of literature. First, it bridges creative destruction – a familiar notion in economic growth theory (e.g. Segerstrom et al., 1990; Grossman and Helpman, 1991; Aghion and Howitt, 1992; Helpman and Trajtenberg, 1994) – and asset pricing. Accordingly, we contribute to the literature that investigates the effects of technological innovations on asset prices (cf. Nicholas, 2008; Hsu, 2009; Comin et al., 2009; Pástor and Veronesi, 2009; Gârleanu et al., 2012b). The paper by Gârleanu et al. (2012a) is most closely related to ours. They propose a general-equilibrium overlapping-generations model in which innovation erodes the human capital of older workers, thus creating a "displacement risk factor". Since the rents of technological innovations are earned by future cohorts of investors, existing agents cannot use financial markets to avoid the displacement effect.

Second, we incorporate creative destruction risk into Merton's (1973) ICAPM, to argue that investment opportunities change when inventions render existing businesses obsolete. In this sense, we extend existing empirical tests of the ICAPM (e.g. Campbell, 1993, 1996; Campbell and Vuolteenaho, 2004; Brennan et al., 2004). Third, our study complements the literature that aims to explain the value premium. For example, in Zhang's (2005) model, costly reversibility and a countercyclical price of risk generate the value premium, and Petkova and Zhang (2005) show that time-varying risk moves in the appropriate direction to explain the value premium. Fourth, we extend studies that associate size- and B/M-ratios with firm-specific measures of distress (e.g. Chan, Chen, and Hsieh, 1985; Chan and Chen, 1991; Fama and French, 1995) by proposing a connection to an aggregate distress factor.

The remainder of this paper is organized as follows. In Section 2 we introduce a theoretical framework that relates invention activity to asset prices. Section 3 contains a description of the data, and we motivate the choice of the risk factor proxy. We discuss econometric issues in Section 4.1 and present the results of our main empirical analysis in Section 4.2. Here we adopt a long-run perspective using annual data. In Section 4.3.1 we introduce an invention-mimicking portfolio that we use for robustness checks and model specification tests. With Section 4.3.2 we test our model on quarterly postwar data. We conclude in Section 5.

2 Theoretical framework

Our theoretical framework links Schumpeter's notion of creative destruction to asset pricing. It formalizes the idea that certain inventions may turn into what Schumpeterian growth theory has dubbed General Purpose Technologies (GPTs), acknowledging their pervasive impact in a wide range of sectors (cf. Helpman and Trajtenberg, 1994). Although GPTs foster economic growth, they also render established technologies and the business models built on them obsolete. Inventions thus represent a latent threat for investments in extant businesses. How do investors account for the ambivalent nature of inventions, and what are the implications for asset pricing? Instead of working in a general equilibrium setup, as in Gârleanu et al. (2012a), we address this question within Merton's (1973) ICAPM framework. The resulting conditional beta model allows estimation and testing using standard empirical asset pricing techniques.

Consider a setting in which a business i generates a random payoff $X_{i,t+1}$, and where N_t inventions occur during $t-1$ and t, each of which may destroy business i with probability π_i. When π_i is small and N_t is large, the number of inventions $D_{i,t+1}$ that destroy business i is conditionally Poisson distributed, with $\lambda_{i,t} = \pi_i N_t$. In the event that business i is destroyed, $D_{i,t+1} > 0$, and $X_{i,t+1}$ equals zero. If the business survives, the expected payoff of business i, conditional on time t information is assumed to be positive. Therefore, we can write

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

where $\mathbb{E}_t[\cdot]$ denotes the expected value conditional on time t information, and $\exp(-N_t\pi_i) = \mathbb{P}_t[D_{i,t+1} = 0]$ the conditional survival probability of business i. Since more inventions have a chance of destroying business i, the conditional expected payoff of business i decreases with an increasing number of inventions, viz

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

The negative effect of invention activity on conditional expected payoffs is stronger for businesses with higher π_i, provided the conditional survival probability is sufficiently high.[1]

The notion that high π_i businesses are more exposed to the risk of creative destruction connects the present study to a literature that identifies small-value firms as distressed. For example, Vassalou and Xing (2004) report a higher default risk for value stocks, and Fama and French (1995) find that value stocks are less profitable than growth stocks. Both Chan et al. (1985) and Vassalou and Xing (2004) evince that small firms have a higher default risk. Chan and Chen (1991) show that small firms tend to operate with a low production efficiency. Those distressed businesses may not survive invention-induced technological changes, in which case the negative impact of invention activity on payoffs appears stronger for small-value stocks. This

[1] Assuming that $\mathbb{E}_t[X_{i,t+1}|D_{i,t+1} = 0] > 0$,

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

is positive for $\pi_i N_t = \lambda_{i,t} > 1$, that is, for $\mathbb{P}_t(D_{i,t+1} = 0) = \exp(-\pi_i N_t) > \exp(-1) = 0.37$.

train of thought establishes the link between idiosyncratic distress, reflected in π_i, and the Schumpeterian risk factor invention activity.

We use Merton's (1973) Intertemporal CAPM to formalize the link between creative destruction risk and asset pricing. That is, we regard invention activity as a state variable that affects investment opportunities through its potentially destructive effects on extant businesses. Suppose that a representative agent with an infinite life span maximizes a standard utility function $U = \mathbb{E}_t \sum_{j=0}^{\infty} \delta^j u(c_{t+j})$, where δ is the subjective discount factor.[2] He consumes c_t of his wealth W_t and invests the remainder into a portfolio of assets that yields the gross return $R_{W,t} = \sum_{i=1}^{n} w_{i,t} R_{i,t}$, where $R_{i,t}$ are gross returns, and $w_{i,t}$ are portfolio weights that sum to 1. The next period's wealth then emerges as $W_{t+1} = R_{W,t+1}(W_t - c_t)$. Following Fama (1970), we can write the investor's maximization problem as

$$\max \mathbb{E}_t \sum_{j=0}^{\infty} \delta^j u(c_{t+j}) = \max u(c_t) + \delta \mathbb{E}_t[V(W_{t+1}, N_{t+1})], \tag{3}$$

where $V(W_{t+1}, N_{t+1})$ denotes the maximized value of the utility function at time $t+1$. Invention activity determines how much the investor benefits from the maximization, and it thus enters the value function. In ICAPM terms, invention activity is a state variable that accounts for shifts in the investment opportunity set.

From the first-order conditions of Equation (3), it follows that the stochastic discount factor (SDF), which prices payoffs through $p_{i,t} = \mathbb{E}_t[m_{t+1} X_{i,t+1}]$, can be expressed as

$$m_{t+1} = \delta \frac{V_W(W_{t+1}, N_{t+1})}{V_W(W_t, N_t)}, \tag{4}$$

[2] The following exposition draws on Cochrane (2005), Ch. 9.

where V_W denotes the partial derivative of the value function with respect to wealth. We can then derive the following approximation for the conditional expected excess return of asset i,[3]

$$
\begin{aligned}
\mathbb{E}_t[r^e_{i,t+1}] &\approx rra_t \mathrm{cov}_t\left[r^e_{i,t+1}, \frac{\Delta W_{t+1}}{W_t}\right] + \gamma_{N,t}\mathrm{cov}_t\left[r^e_{i,t+1}, \frac{\Delta N_{t+1}}{N_t}\right] \\
&= \gamma_t' \mathrm{cov}_t[f_{t+1}, r^e_{i,t+1}],
\end{aligned} \tag{5}
$$

where $r^e_{i,t+1} = R_{i,t+1} - R^f_{t+1}$, with R^f_{t+1} the risk-free rate, $rra_t = -\frac{W_t V_{WW}(W_t,N_t)}{V_W(W_t,N_t)}$, $\gamma_{N,t} = -\frac{N_t V_{WN}(W_t,N_t)}{V_W(W_t,N_t)}$, $f_{t+1} = \left(\frac{\Delta W_{t+1}}{W_t}, \frac{\Delta N_{t+1}}{N_t}\right)'$, and $\gamma_t = (rra_t, \gamma_{N,t})'$.

Alternatively, we can use

$$
\mathbb{E}_t[r^e_{i,t+1}] \approx \beta_{W,i,t}\lambda_{W,t} + \beta_{N,i,t}\lambda_{N,t} = \beta_{i,t}'\lambda_t, \tag{6}
$$

where $\beta_{i,t} = (\beta_{W,i,t}, \beta_{N,i,t})' = \mathrm{var}_t[f_{t+1}]^{-1}\mathrm{cov}_t[f_{t+1}, r^e_{i,t+1}]$, and

$$
\lambda_t = \begin{bmatrix} \lambda_{W,t} \\ \lambda_{N,t} \end{bmatrix} = \mathrm{var}_t[f_{t+1}] \begin{bmatrix} rra_t \\ \gamma_{N,t} \end{bmatrix}. \tag{7}
$$

The SDF then can be approximated by

$$
m_t \approx b_{0,t} + b_{W,t}\frac{\Delta W_{t+1}}{W_t} + b_{N,t}\frac{\Delta N_{t+1}}{N_t}. \tag{8}
$$

Equation (6) is the conditional beta representation of a creative destruction risk asset pricing model (CDRM), which accounts for the possibility that investments with greater exposure to creative destruction risk require compensation in the form of a higher expected return. Because serendipitous invention activity poses a generic

[3] For that purpose, write the investor's optimization problem in continuous time, such that Equation (5) emerges as a discrete time approximation of the expected return representation in continuous time.

threat to investments in existing firms, we would expect that $\gamma_{N,t} = -\frac{N_t V_{WN}(W_t, N_t)}{V_W(W_t, N_t)} < 0$. Put differently, a payoff equal to the value of de-meaned invention growth has a positive price, viz

$$p\left[\frac{\Delta N_{t+1}}{N_t} - \mathbb{E}_t\left[\frac{\Delta N_{t+1}}{N_t}\right]\right] = -\lambda_{N,t} > 0, \tag{9}$$

such that stocks with negative invention betas must offer higher expected returns. The CDRM thus formalizes the idea that creative destruction associated with and rooted in invention activity is a systematic risk for extant businesses; it is neither traded nor entirely insurable. This notion warrants some discussion.

First, this Schumpeterian view of invention activity does not necessarily apply to the efforts of R&D departments, whose work is directed toward protecting and improving the firm's products to gain or maintain a competitive edge. Their effort is distinct from the potentially destructive side of undirected invention activity that we accentuate.

Second, new business models may arise, as few of the myriad of inventions serendipitously turn into GPTs, but those that do generally are not discernible when they occur, so even savvy venture capitalists cannot reap profits from them. In the same vain, in the overlapping-generations model of Gârleanu et al. (2012a), existing agents cannot use financial instruments to hedge against the downside effects of technological innovations. Economic rents are reaped by future generations, who can invest in those businesses that inventions will create, while existing agents have to bear the erosion of their human capital.

Third, the CDRM does retain the paradigm that the covariance of asset returns with changes in wealth/consumption determines equilibrium expected returns. Yet those parts of W that result from investments in extant businesses are imperiled by invention-induced creative destruction. The CDRM thus corrects the potential mis-pricing that might result from the sole use of the wealth portfolio return in the SDF in Equation (8) and the expected return-beta representation (6).

3 Data

To conduct an empirical assessment of whether creative destruction risk matters for asset pricing, we need a proxy for invention activity. R&D expenditures come to mind, but these data measure cost, not outcomes. We instead choose patenting activity as an outcome-oriented proxy, drawing on Jovanovic and Rousseau (2005) who associate patenting activity with the arrival and spread of GPTs. To obtain suitable data we contacted the U.S. Patent and Trademark Office (USPTO), which granted us access to its master file of issued patents. The data contain an entry for each patent issued at a specific date, spanning the period from 1790 to 2008. Even though the USPTO data offer more detail (for recent periods at least), we compute the obvious proxy for invention activity, N_t, as the number of patents issued between $t-1$ and t. The net growth rate of patenting activity, denoted pg, then approximates $\frac{\Delta N}{N}$ in Equation (5).

One could imagine a more sophisticated proxy for invention activity. For example, because certain inventions exert a greater future impact than others, one could try to filter out those patents that emerged as significant ex post. Tracking subsequent patent citations is indeed important for measuring the technological impact of a specific invention (Nicholas, 2008). However, this issue loses some relevance when accounting for creative destruction risk in asset pricing. In hindsight, one could observe the success or failure of an invention and try to measure its subsequent impact. However, we are interested in the ex ante probability that an invention will destroy existing businesses. This is the threat that owners face and it seems prudent to assume that no investor can envision, at the time of its issuance, a specific patent's future impact. Laser technology, for example, revolutionized medicine, media, warfare, and telecommunication alike; it exemplifies the serendipitous effects of an invention, which were unforeseeable ex ante (Townes, 2003). Accordingly, we believe that the overall number of patents is a suitable indicator to capture our notion of creative destruction risk.

Yet patents still represent an imperfect proxy for the kind of invention activity that we are interested in. A considerable share of patenting activity aims solely to preserve extant businesses and their products. Ideally, one would filter out those protective/conservative patents, to focus on genuinely undirected, potentially destructive inventions. However, this intricate task would need to be based on assailable assumptions, which we chose to forgo. By using an unrefined proxy, we also avoid the criticism of going fishing for a factor that proves to be ex post empirically significant.

We use the simple return of the value-weighted NYSE, AMEX and NASDAQ traded stocks, denoted r_W, as a proxy for $\frac{\Delta W}{W}$. The test assets in our main analysis are the excess returns (over the one-month T-Bill rate) of the 25 size- and B/M-sorted Fama-French portfolios. We use both value-weighted (VWP) and equally-weighted (EWP) portfolios. These data are retrieved from Kenneth French's financial data library, which is also the source for the Fama-French factors *SMB* and *HML*.[4] excess return of a "size" investment strategy that is long in small stocks and short in large stocks. For details on the construction of *SMB* and *HML* from six base portfolios, see Fama and French (1993).

[4]See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html, accessed March 22, 2013. N.b. that due to frequent changes in the CRSP base data, newer downloads will yield somewhat different return series.

For our main analysis, we use annual data, starting from 1927, the first year for which Fama-French portfolios are available, and running until 2008, the final date in our USPTO master file. We adopt this long-run, low frequency perspective for two reasons. First, our proxy for invention activity is prone to measurement errors. The number of patents recorded during a certain period depends on the USPTO's institutional settings and backlogs in the patent issuing process. These disturbances become aggravated at higher sampling frequencies. Second, a longer time-series can capture more periods of creative destruction.

[Insert Table 1 about here]

[Insert Table 2 about here]

In Table 1 we report descriptive statistics on patenting growth, market return, and the two Fama-French factors; Figure 1 shows a time-series plot of these data. The average return of the market portfolio proxy amounts to 11.4 percent per year. The average excess returns of the size and value investment strategies are 3.6 percent (*SMB*) and 5.1 percent (*HML*), respectively. Considerable size and value effects become also apparent in Table 2, which reports the means and standard deviations of the excess returns of the size- and B/M-sorted test portfolios. From left to right, value firms earn more on average than growth firms; from top to bottom, small firms earn more on average than large firms. The small-growth VWP, with an average annual excess return of 3.7 percent, is a notorious exception.

[Insert Figure 1 about here]

A descriptive analysis of the time-series of patenting growth, *HML* and *SMB* reveals some interesting empirical facts. As Table 1 shows, patenting growth exhibits no serial correlation and averages at 2.4 percent annually with a standard deviation comparable to that of *SMB* and *HML*. Furthermore, patenting growth is negatively correlated with the Fama-French factors. Figure 1 depicts several patenting activity peaks during the 1950s and 1960s, when inventions in the field of electronics, petrochemicals, and aviation emerged, as well as the late 1990s, reflecting inventions in the field of information systems. Bursts of patenting activity tend to be accompanied by low *HML* and *SMB* returns. In contrast, periods marked by low invention activity, such as the 1970s, tend to be associated with higher *SMB* and *HML* returns.

4 Estimation results and discussion

4.1 Empirical methodology

Similar to any conditional asset pricing model, the conditional CDRM derived above is subject to the Hansen-Richard critique. It is not empirically testable without further assumptions. To avoid this concern, we could follow Cochrane (1996), and specify the time-varying SDF parameters in Equation (8) as affine functions of instruments available at time t. Doing so would yield a scaled factor model that can be conditioned to empirically useable moment conditions. However, at this stage we do not want to mix the effects of scaling variables with the Schumpeterian risk-factor invention activity. Instead, we assume that an unconditional beta representation of the conditional CDRM in Equation (6) exists, such that

$$\mathbb{E}[r_{i,t}^e] = \beta_{W,i}\lambda_W + \beta_{N,i}\lambda_N = \beta_i'\lambda, \tag{10}$$

where $\beta_i = (\beta_{W,i}, \beta_{N,i})' = \text{var}(f_t)^{-1}\text{cov}(f_t, r_{i,t}^e)$ and $\lambda = (\lambda_W, \lambda_N)' = \mathbb{E}[\lambda_t]$.[5] Using the risk factor proxies, we now have $f_t = (r_{W,t}, pg_t)'$. Alternatively, we can write Equation (10) in its SDF representation,

$$\mathbb{E}[m_t r_{i,t}^e] = 0 \tag{11}$$

$$m_t = b_0 + b_W r_{W,t} + b_N pg_t. \tag{12}$$

The unconditional moment restrictions in Equation (11) can be tested using the first-stage Generalized Method of Moments (GMM) J-statistic, and time-series regressions of the test assets' excess returns on the factor proxies and a constant yield estimates of $\beta_{W,i}$ and $\beta_{N,i}$ in Equation (10). The estimated betas serve as explanatory variables in a cross-sectional regression that uses the average excess returns of the test assets as dependent variables, and that estimates λ_W and λ_N as cross-sectional regression slopes.

For statistical inference we follow Cochrane (2005), who suggests treating this two-pass regression setup as an instance of GMM. The GMM approach offers the following advantages. First, statistical inference can be based on somewhat less restrictive assumptions than Shanken's (1992) more widely used formulas.[6] Second, we can assess the statistical significance of the estimated risk compensations associated with creative destruction ($\hat{\beta}_{N,i} \cdot \hat{\lambda}_N$) using the joint covariance matrix of the first- and second-step estimates delivered by GMM theory (cf. Hansen, 1982), and by

[5] Unless the data generating process is i.i.d., a conditional beta representation $\mathbb{E}_t[r_{i,t}^e] = \beta_{i,t}'\lambda_t$ does not necessarily imply an unconditional counterpart $\mathbb{E}[r_{i,t}^e] = \beta_i'\lambda$. The conditions for the existence of the latter, given the former are outlined for the single factor case by Singleton (2006), and Lewellen and Nagel (2006). Similar conditions can be stated for conditional two-factor models such as the CDRM of Equation (6). We assume that these conditions are fulfilled and base our econometric work on the unconditional beta representation (10) and the unconditional moment conditions (11).

[6] There is no need to assume independence of factors and first-step regression disturbances, and one can account for serial correlation among the regression residuals.

applying the delta method. Third, the GMM approach can be extended to account for the initial estimation of the weights of a mimicking portfolio, and for convenient model specification tests (see Section 4.3). The methodological details appear in the Appendix.[7]

4.2 Explaining size and value premia with the CDRM

Table 3 (VWP) and Table 4 (EWP) display the results of the first-step time-series regressions. Panels A report the beta estimates, the associated t-statistics, and the time-series R^2. The invention betas vary considerably across test assets following a clear-cut cross-sectional pattern. Large negative $\hat{\beta}_N$ cluster in the upper right corner of the respective panels, where small and high B/M portfolios are located. The small-value portfolio has the strongest negative exposure to invention activity, whereas the invention betas for the large-growth portfolios are positive. Panels B of Table 3 and Table 4 show that the estimates of λ_N have the presumed negative sign, and they are statistically significant with p-values of 1.8 percent (WVP) and 1.2 percent (EWP), respectively.[8]

[Insert Table 3 about here]

[Insert Table 4 about here]

[Insert Table 5 about here]

In a recent paper, Maio and Santa-Clara (2012) recommend checking the plausibility of the estimated ICAPM-implied relative risk aversion coefficients (rra) to exploit their relation to the factor risk premia λ (see Equation 7). Assuming constant

[7]A GAUSS program that implements these procedures and that produces the results reported herein is available on request.

[8]Unless noted otherwise, the reported p-values were obtained from a $t-$test of the null hypothesis that the true parameter is zero.

relative risk aversion, and that $\gamma_{N,t} = \gamma_N$, as well as that the unconditional CDRM (10) holds, we can use the estimate[9]

$$\begin{bmatrix} \widehat{rra} \\ \hat{\gamma}_N \end{bmatrix} = \left[\frac{1}{T} \sum_{t=1}^{T} f_t^* f_t^{*'} \right]^{-1} \begin{bmatrix} \hat{\lambda}_W \\ \hat{\lambda}_N \end{bmatrix}. \tag{13}$$

Using the results from Table 3 (VWP), we obtain $\widehat{rra} = 1.22$ (s.e. 0.58), which is an economically plausible estimate. The same holds for the EWP-based results of Table 4, which imply $\widehat{rra} = 1.02$ (s.e. 0.61).

Table 5 shows that the estimated risk compensations associated with creative destruction risks ($\hat{\beta}_{N,i} \cdot \hat{\lambda}_N$) are economically substantial. Large positive and statistically significant $\hat{\beta}_{N,i} \cdot \hat{\lambda}_N$ cluster where small and high B/M portfolios are located, while the estimated risk compensation associated with creative destruction risk is negative for the large-growth portfolios. Using value-weighted test portfolios, we estimate an additional expected excess return compensation of 6.8 percentage points per annum for the small-value portfolio (p-value 0.3 percent). For the large-growth portfolio, we estimate an expected return discount of -2.0 percentage points (p-value 7.6 percent). These results are more pronounced for equally-weighted portfolios (Panel B in Table 5): for the small-value portfolio we estimate an 11.3 percentage point risk compensation (p-value 0.06 percent), whereas we predict a -2.4 percentage points expected return discount (p-value 1.8 percent) for the large-growth portfolio. These differences in the expected excess return compensation for portfolios with the highest positive versus the lowest negative exposure to creative destruction risk are highly significant. The p-values are 0.3 percent (VWPs) and 0.01 percent (EWP).

[9]Since then

$$\mathbb{E}(\lambda_t) = \lambda = \begin{bmatrix} \lambda_W \\ \lambda_N \end{bmatrix} = \mathbb{E}\left[\mathbb{E}_t [f_{t+1}^* f_{t+1}^{*'}] \right] \begin{bmatrix} rra \\ \gamma_N \end{bmatrix},$$

where $f_{t+1}^* = f_{t+1} - \mathbb{E}_t[f_{t+1}]$. Assuming that $\mathbb{E}_t[f_{t+1}] = \mathbb{E}[f_{t+1}]$ suggests the estimate in Equation (13).

These results are consistent with our reasoning that small-value stocks have a high destruction probability π_i and are thus imperiled by bursts in invention activity, and that investors must be compensated for bearing that risk. By contrast, large-growth firms, which are characterized by strong earnings growth and high profitability ratios, are more likely to withstand periods of creative destruction. An investment in large-growth stocks thus provides protection against creative destruction risk, hence the expected return discount.

[Insert Table 6 about here]

Table 6 and Figures 2 and 3 illustrate the results of a comparison of the empirical fit of the CDRM with the static CAPM and the Fama-French (1995) model. The static CAPM, for which we use the same wealth portfolio proxy, constitutes a special case of the CDRM, for which the investment opportunity set is unaffected by invention activity. The Fama-French model with *SMB*, *HML*, and the excess return of the wealth portfolio proxy (r^e_W) as risk factors is the obvious benchmark.

Such a comparison should not be seen as a race for the best goodness of fit. As Cochrane (2008) recognizes, portfolio-based models such as the Fama-French model have a head start when estimated using size- and B/M-sorted portfolios, which exhibit a correlation structure that is well captured by three principal components (cf. Lewellen et al., 2010). Static CAPM and the Fama-French model instead serve as reference points for assessing the ability of the CDRM to empirically account for size and value premia.[10]

Table 6 reports the λ-estimates and J-test results for the three models, along with the cross-sectional R^2. The results for the static CAPM and Fama-French model are unsurprising. Panel A (VWP) and Panel B (EWP) of Table 6 show that the R^2

[10] Estimation of static CAPM and Fama-French model makes use of the GMM approach towards two-pass regression described above.

of the static CAPM are quite low, 24 percent for VWP and 49 percent for EWP, and the J-tests reject the CAPM at conventional levels of significance. The Fama-French model's R^2 are considerably higher, at 71 percent (VWP) and 83 percent (EWP). The J-tests reject the Fama-French model at five percent, but not at the one percent significance level. The CDRM also delivers a substantial improvement over the static CAPM, with R^2 increases of 27 percentage points (VWP) and 24 percentage points (EWP). The CDRM's R^2 are remarkably high, considering the parsimonious use of a single non-financial factor. The J-test results for the CDRM are similar – in terms of being borderline cases – to those of the Fama-French model.

[Insert Figure 2 about here]

[Insert Figure 3 about here]

Figures 2 (VWP) and 3 (EWP) illustrate the models' goodness of fit by depicting the average excess returns against the model-implied excess return estimates. The Panel A plots reveal the notorious deficiency of the static CAPM to account for cross-sectional average return differences across size- and B/M-sorted portfolios. The Fama-French model (Panel B) is naturally more successful, but the CDRM (Panel C) also improves the empirical fit considerably. The similarity of the CDRM's and Fama-French model's pricing error plots for the equally-weighted portfolios is remarkable. The CDRM does a particularly good job in pricing small-value portfolios. We have argued above that small-value firms are those with the highest risk of becoming obsolete through creative destruction. The premium for creative destruction risk corrects, to some extent, for the resulting mis-pricing of the CAPM.[11]

[11]Both Fama-French model and CDRM cannot account for the small average excess return of the small-growth portfolio, which poses a long-standing challenge for empirical asset pricing (cf. Campbell and Vuolteenaho, 2004; Yogo, 2006). D'Avolio (2002), Mitchell et al. (2002) and Lamont and Thaler (2003) document limits to arbitrage due to short-sale constraints, which may be the reason that it is difficult to price the small-growth portfolio.

4.3 Robustness checks

4.3.1 Mimicking portfolio CDRM and model specification tests

The results reported in the previous section evince that creative destruction risk has a role in asset pricing. However Lewellen et al. (2010) add the caveat that achieving small pricing errors on the size- and B/M-sorted test portfolios should not be overemphasized. They call for greater diligence when assessing a model's ability to account empirically for value and size premia. We therefore subject the CDRM to additional model specification tests. However, these tests require the risk factors to be excess returns, which is not the case for the CDRM, in that invention growth will not have a zero price. We therefore replace the risk factor proxy *patenting growth* by the excess return of its mimicking portfolio (cf. Breeden et al., 1989).

Following Vassalou (2003), we obtain the mimicking portfolio weights from a projection of invention growth on the space spanned by the excess returns (over the one-month T-Bill rate) of the six base assets that are used to construct *HML* and *SMB* (for details see Fama and French, 1993).[12] This entails an OLS estimation of the regression equation,

$$pg_t = \gamma_0 + \sum_{i=1}^{6} \gamma_b r^e_{B,i,t} + v_t, \tag{14}$$

where $r^e_{B,i,t}$ denotes the excess return of base asset i. The maximum correlation portfolio that mimics patenting growth uses the estimated slope coefficients as portfolio weights. The mimicking portfolio's excess return

$$r^e_{M,t} = \sum_{i=1}^{6} \hat{\gamma}_i r^e_{B,i,t} \tag{15}$$

[12]These data come from Kenneth French's data library.

then serves as an alternative proxy for invention growth. The factor-mimicking portfolio retains the pricing information of the original factor, but it is less prone to measurement error, and it conveniently comes in the form of an excess return.

[Insert Table 7 about here]

[Insert Table 8 about here]

Table 7 shows that the estimated mimicking portfolio weights are jointly significant, though multicollinearity limits estimation precision.[13] The pattern of the portfolio weights still is noteworthy: the invention-mimicking portfolio takes long positions in large and growth stocks and is short in small and value stocks, which is quite the opposite of *HML* and *SMB*. Furthermore, Table 8 shows that the mean of $r^e_{M,t}$ is negative. The invention-mimicking portfolio can thus be interpreted as a hedge against creative destruction risk.

After replacing patenting growth with the invention-mimicking portfolio's excess return $r^e_{M,t}$ from Equation (15), we re-estimate the parameters of the modified expected return-beta representation of the CDRM,

$$\mathbb{E}[r^e_{i,t}] = \beta_{W,i}\lambda_W + \beta_{M,i}\lambda_M = \tilde{\beta}_i'\tilde{\lambda}, \tag{16}$$

where $\tilde{\beta}_i = (\beta_{W,i}, \beta_{M,i})' = \text{var}[\tilde{f}_t]^{-1}\text{cov}[\tilde{f}_t, r^e_{i,t}]$, $\tilde{f}_t = \left(r_{W,t}, r^e_{M,t}\right)'$, and $\tilde{\lambda} = (\lambda_W, \lambda_M)'$. We refer to Equation (16) as the Mimicking Portfolio CDRM. Since $r^e_{M,t}$ is an excess return, it follows that $\lambda_M = \mathbb{E}[r^e_{M,t}]$, a fact that Lewellen et al. (2010) suggest using for a model specification test. Their test statistic is the difference between $\hat{\lambda}^{CS}_M$, the estimate of λ_M from the second step of the two-pass regression, and the time-series estimate $\hat{\lambda}^{TS}_M = \frac{1}{T}\sum_{t=1}^{T} r^e_{M,t}$. Large absolute deviations of $\Delta\hat{\lambda} = \hat{\lambda}^{CS}_M - \hat{\lambda}^{TS}_M$ from zero indicate model misspecification.

[13] This is a common result in mimicking-portfolio regressions (cf. Lamont, 2001; Vassalou, 2003).

To obtain the limiting distribution of the test statistic $\Delta\hat{\lambda}$, we have to account for three peculiarities: the mimicking portfolio weights are estimated, the beta estimates come from a subsequent time-series regression step, and $\hat{\lambda}_{CS}$ and $\hat{\lambda}_{TS}$ are correlated. Therefore, we collect all model-implied moment restrictions, namely, the orthogonality conditions from the regression that gives the portfolio weights, those from the time-series regressions that yield the beta estimates, and the moment conditions that identify $\hat{\lambda}_M^{CS}$ and $\hat{\lambda}_M^{TS}$. We can then conceive of the problem as an instance of GMM. GMM theory gives the limit distribution and the asymptotic covariance matrix of the estimates, from which follows the distribution of $\Delta\hat{\lambda}$ under the null hypothesis that $\lambda_M = \mathbb{E}[r^e_{M,t}]$. The Appendix outlines the methodological details.

[Insert Table 9 about here]

[Insert Table 10 about here]

Tables 9 (VWP) and 10 (EVP) report the estimation results for the Mimicking Portfolio CDRM. The pattern of beta estimates and the risk compensations correspond to those of the main analysis (cf. Tables 3 and 4), except that the Mimicking Portfolio CDRM even improves the estimation precision. The risk compensation estimates associated with creative destruction also become more significant, from both economic and statistical perspectives (compare Table 11 with Table 5).

Figure 4 shows that the Mimicking Portfolio CDRM further improves the goodness of fit, and also a remarkable similarity between the pricing error plots of Fama-French model and CDRM. This is also reflected in the CDRM's cross-sectional R^2, which come close to the values from the Fama-French model: 81.1% vs. 83.4% for EVPs and 65.4% vs. 70.5% for VWPs. The explanation for these sharpened results is that the invention-mimicking portfolio alleviates measurement errors in the patenting data.

[Insert Figure 4 about here]

Using value-weighted portfolios as test assets, we obtain $\hat{\lambda}_M^{CS} = -0.021$ (p-value 0.5 percent). With an average excess return of the mimicking portfolio of $\hat{\lambda}_M^{TS} = -0.017$ (p-value 6.4 percent), $\Delta\hat{\lambda}$ is not significantly different from zero (p-value 56.1 percent). Using EVPs as test assets reveals no evidence of model misspecification either. In this case, $\hat{\lambda}_M^{CS} = -0.026$ (p-value 0.4 percent), and the p-value for $\Delta\hat{\lambda}$ is 33.5 percent.

Lewellen et al. (2010) also argue that a model that aims to explain size and value premia should not be evaluated solely on the 25 size- and B/M-sorted portfolios; it also requires an assessment of whether it can price *HML* and *SMB*, too. However, a two-pass regression of the CDRM that uses the Fama-French factors as test assets cannot deliver testable restrictions because the number of test assets equals the number of risk factors. We circumvent this problem by using the Mimicking Portfolio CDRM and the statistic $\Delta\hat{\lambda}$ for a model specification test. Using the two Fama-French factors instead of size- and B/M-sorted portfolios as test assets, we obtain a similar but less precise estimate $\hat{\lambda}_M^{CS} = -0.024$ (p-value 11.4 percent). Furthermore, $\Delta\hat{\lambda} = -0.007$, which is, given a p-value of 69.2 percent, not significantly different from zero.

We conclude this section by noting that that none of the model specification tests provides evidence against the CDRM. Considering that it also passes Maio and Santa-Clara's (2012) plausibility check, by delivering an economically sensible relative risk aversion estimate, the empirical results reported so far strengthen the conclusion that creative destruction indeed plays a role in asset pricing.

4.3.2 Postwar sample

We have adopted a long-run, low frequency perspective to capture more periods of creative destruction and avoid measurement errors in the patenting data. However, most empirical tests of asset pricing models instead use postwar data sampled at quarterly frequencies. To achieve comparable results, as well as provide an additional robustness check, we also estimate the CDRM using quarterly data from 1950:Q1-2008:Q4. We report the results for the value-weighted size- and B/M-sorted portfolios; the results are quite similar for equally-weighted test assets. Furthermore, we use the Mimicking Portfolio CDRM in order to alleviate measurement errors in the patenting data, which are aggravated at higher sampling frequencies.

[Insert Table 12 about here]

[Insert Table 13 about here]

The results in Tables 12 and 13 confirm the conclusions of the main analysis. Invention growth betas exhibit the same cross-sectional pattern as in Table 3. Large negative invention betas cluster where small and high B/M portfolios are located, and the sole positive, statistically significant invention beta estimate refers to the large-growth portfolio. Again, $\hat{\lambda}_M$ is negative and statistically significant. Table 13 shows that the cross-sectional pattern, size, and statistical significance of the estimated compensations for creative destruction risk are comparable to those in the long-run/low-frequency analysis (cf. Table 13 with Panel A of Table 5). Panel B of Table 12 further shows that the test statistic $\Delta\hat{\lambda}$ is not significantly different from zero, so the CDRM passes Lewellen et al's (2010) model specification test. Overall, the storyline based on the higher frequency, postwar sample results remains unchanged. Neither the Great Depression nor World War II drive the conclusions regarding the role of creative destruction risk in asset pricing.

5 Conclusion

Consider the range of technological changes in the past century. Creative destruction processes have been pivotal for economic growth, but they also have presented substantial risks for investments in extant firms. Imagine a John Doe, born in 1940, who started to work at the age of 20, and then started investing. This investment start would have occurred in the midst of the technological revolution of the 1950s and 1960s. Assuming a retiring age of 65, J.D. then would have started to consume his savings in 2005, after the peak of an information technology wave. At this point, he would still have had a life expectancy of 19 years.[14] During the course of his life, among the myriad of inventions, some have turned into General Purpose Technologies, and a plethora of businesses have become obsolete because of them. Creative destruction thus has posed a considerable risk for J.D.'s past investments, and it will continue to be in his retirement years.

As our study shows, part of the cross-sectional return differences across size- and B/M-sorted portfolios can be explained as premia for bearing or hedging against creative destruction risk. The empirical results presented in this paper suggest it is a risk for which investors demand sizable expected return compensations. Our findings thus extend prior studies that have identified small-value firms as under distress. An investment in small-value firms, with their operational inefficiencies and lower likelihood of weathering GPT-induced changes, exposes investors to the risk of creative destruction, and in return, investors demand compensation. An investment in large-growth firms instead provides some protection against creative destruction risk.

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

Our conclusions are consistent with several findings related to size and value effects. They emphasize that *HML* and *SMB* are measures of distress (e.g. Chan et al., 1985; Chan and Chen, 1991; Fama and French, 1995; Vassalou and Xing, 2004), and they augment the findings of Liew and Vassalou (2000) and Vassalou (2003), who show that *HML* and *SMB* forecast GDP growth. The same process that triggers economic growth also threatens existing businesses.

Just as Fama (1991, p. 1610) concluded, “In the end, I think we can hope for a coherent story that [...] relates the behavior of expected returns to the real economy in a rather detailed way”, we hope that our study adds a useful paragraph to such a story, relating asset prices to a fundamental risk: the risk of creative destruction.

A Appendix: Details on statistical inference

Cochrane (2005) proposes treating the two-pass regression method that is used to estimate linear factor models as an instance of GMM, which amounts to collecting the moment conditions and their implicit weighting within two regressions. We briefly review Cochrane's idea as it applies to estimating the unconditional CDRM and then turn to the extensions presented in the main text.

The generic GMM problem considered by Hansen (1982) involves finding the $\hat{\theta}$ that solves

$$a_T(\hat{\theta})g_T(\hat{\theta}) = 0, \tag{A-1}$$

where $\hat{\theta}$ is a $(P \times 1)$-vector of parameter estimates, and $g_T(\hat{\theta}) = \frac{1}{T}\sum_{t=1}^{T} u_t(\hat{\theta})$. $u_t(\cdot)$ is an $(M \times 1)$-vector of random functions, such that $\mathbb{E}[u_t(\theta_0)] = 0$, where θ_0 denotes the true parameter vector. Moreover, $a_T(\cdot)$ is of dimension $P \times M$, i.e., P linear combinations of the sample moments $g_T(\hat{\theta})$ are set to zero.

In the two-pass regression framework for the CDRM using K test assets, we have

$$u_t(\theta) = \begin{bmatrix} \begin{bmatrix} \varepsilon_{1,t} \\ \vdots \\ \varepsilon_{K,t} \end{bmatrix} \otimes \begin{bmatrix} 1 \\ f_t \end{bmatrix} \\ r^e_{1,t} - \beta_{W,1}\lambda_W - \beta_{N,1}\lambda_N \\ \vdots \\ r^e_{K,t} - \beta_{W,K}\lambda_W - \beta_{N,K}\lambda_N \end{bmatrix}, \tag{A-2}$$

where $\varepsilon_{i,t} = r^e_{i,t} - \alpha_i - \beta_i' f_t$, $f_t = (r_{W,t}, pg_t)'$, and $\beta_i = (\beta_{W,i}, \beta_{N,i})'$ for $i = 1, \ldots, K$. The parameter vector θ is thus given by

$$\theta = [\alpha_1, \ldots, \alpha_K, \beta_{W,1}, \ldots, \beta_{W,K}, \beta_{N,1}, \ldots, \beta_{N,K}, \lambda_W, \lambda_N]'.$$

Furthermore,

$$a_T(\theta) = \begin{bmatrix} & & & 0 & \cdots & 0 \\ & I_{3K} & & \vdots & \ddots & \vdots \\ & & & 0 & \cdots & 0 \\ 0 & \cdots & 0 & \beta_{W,1} & \cdots & \beta_{W,K} \\ 0 & \cdots & 0 & \beta_{N,1} & \cdots & \beta_{N,K} \end{bmatrix}, \tag{A-3}$$

where I_{3K} is the $3K$ dimensional identity matrix. If $\hat{\theta} \underset{p}{\rightarrow} \theta_0$, we can use the result that for the estimate $\hat{\theta}$, which solves Equation (A-1), we have

$$\sqrt{T}(\hat{\theta} - \theta_0) \underset{d}{\rightarrow} N\left(0, [ad]^{-1} a S a' \left[[ad]^{-1}\right]'\right), \tag{A-4}$$

where $a_T \underset{p}{\rightarrow} a$, $S = \mathbb{E}\left[u_t(\theta_0) \cdot u_t(\theta_0)'\right]$, $d = \mathbb{E}\left[\left.\frac{\partial u_t(\theta)}{\partial \theta'}\right|_{\theta_0}\right]$ (cf. Hansen, 1982).[15]
For applied work, we use

$$\widehat{\text{var}}(\hat{\theta}) = \frac{(\hat{a}\hat{d})^{-1}\hat{a}\hat{S}\hat{a}'((\hat{a}\hat{d})^{-1})'}{T}, \tag{A-5}$$

where

$$\hat{a} = a_T(\hat{\theta}), \qquad \hat{d} = \left.\frac{\partial g_T(\theta)}{\partial \theta'}\right|_{\theta=\hat{\theta}}, \qquad \hat{S} = \frac{1}{T}\sum_{t=1}^{T} u_t(\hat{\theta})u_t(\hat{\theta})'.$$

The t-statistics reported in Tables 9 and 10 are based on these formulas.

Since GMM theory gives the joint covariance matrix of the estimates, we can apply the delta method to obtain the limit distribution and asymptotic variance of the risk compensation estimates, e.g. those associated with creative destruction, $\hat{\beta}_{N,i} \cdot \hat{\lambda}_N$. The t-statistics reported in Table 11 are obtained this fashion.

Section 4.3.1 extends this approach to account for an initial estimation of the weights of a mimicking portfolio and for the computation of the cross-sectional and

[15] Assuming serially uncorrelated $u_t(\theta_0)$ and that regularity conditions hold.

time-series estimates of λ_M. Conceiving of the problem as an instance of GMM, we collect all moment conditions, which now imply

$$u_t(\theta) = \begin{bmatrix} v_t \begin{bmatrix} 1 \\ r^e_{B,t} \end{bmatrix} \\ \gamma' r^e_{B,t} - \lambda^{TS}_M \\ \begin{bmatrix} \varepsilon_{1,t} \\ \vdots \\ \varepsilon_{K,t} \end{bmatrix} \otimes \begin{bmatrix} 1 \\ f_t \end{bmatrix} \\ r^e_{1,t} - \beta_{W,1}\lambda_W - \beta_{M,1}\lambda^{CS}_M \\ \vdots \\ r^e_{K,t} - \beta_{W,K}\lambda_W - \beta_{M,K}\lambda^{CS}_M \end{bmatrix}, \tag{A-6}$$

where

$$\begin{aligned} v_t &= pg_t - \gamma_0 - \gamma' r^e_{B,t}, \\ r^e_{B,t} &= \left(r^e_{B,1,t}, \ldots, r^e_{B,6,t}\right)', \\ \gamma &= (\gamma_1, \ldots, \gamma_6)', \\ \varepsilon_{i,t} &= r^e_{i,t} - \alpha_i - \beta_i' f_t, \\ \beta_i &= (\beta_{W,i}, \beta_{M,i})', \\ f_t &= \left(r_{W,t}, \gamma' r^e_{B,t}\right)', \end{aligned}$$

such that

$$\theta = \left(\gamma_0, \gamma_1, \ldots, \gamma_6, \alpha_1, \ldots, \alpha_K, \beta_{W,1}, \ldots, \beta_{W,K}, \beta_{M,1}, \ldots, \beta_{M,K}, \lambda_W, \lambda^{CS}_M, \lambda^{TS}_M\right)'.$$

Furthermore,

$$a_T(\theta) = \begin{pmatrix} & & & 0 & \cdots & 0 \\ & I_{3K+8} & & \vdots & \ddots & \vdots \\ & & & 0 & \cdots & 0 \\ 0 & \cdots & 0 & \beta_{W,1} & \cdots & \beta_{W,K} \\ 0 & \cdots & 0 & \beta_{N,1} & \cdots & \beta_{N,K} \end{pmatrix}. \tag{A-7}$$

Using (A-6) and (A-7) in Equation (A-5) ensures proper inference for the risk compensation and λ-estimates, as well as for the derivation of the limit distribution of Lewellen et al.'s (2010) test statistic $\Delta\hat{\lambda} = \hat{\lambda}_M^{CS} - \hat{\lambda}_M^{TS}$ under the null hypothesis that $\lambda = \mathbb{E}[r_{M,t}^e]$. Our main analysis uses the excess returns of the Fama-French portfolios as test assets; in this case, $K = 25$. We also use SMB and HML as test assets, in which case $K = 2$. The test statistics reported in Tables 9, 10, 11, 12 and 13 make use of this procedure.

In all instances, we conceive the sequence of (two or three) regressions as a generic GMM problem and thus find $\hat{\theta}$ that solves Equation (A-1). Computing the parameter estimates in this fashion may be somewhat cumbersome, and it is not necessary in the first place. The estimates are identical to those obtained by performing the regressions subsequently.

A GAUSS program, which contains an implementation of the procedures described above, is available on request.

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Tables and Figures

Table 1: Risk Factor Proxies: Descriptive Statistics

The table reports the means (percentage), standard deviations, first-order autocorrelations (ρ), and correlations of the market return proxy (r_W), *SMB*, *HML*, and patenting growth (pg). The sample period is 1927-2008, and the sampling frequency is annual.

			Correlations			
	Mean×100	Std. Dev.×100	r_W	*HML*	*SMB*	ρ
r_W	11.4	20.7				0.04
HML	5.1	14.0	0.12			-0.01
SMB	3.6	14.4	0.40	0.08		0.28
pg	2.4	13.7	-0.06	-0.21	-0.21	0.00

Table 2: Portfolio Excess Returns: Descriptive Statistics
The table shows the summary statistics for yearly excess returns (percentage) of the 25 size- (vertical) and B/M- (horizontal) sorted portfolios from 1927-2008.

Panel A: Value-Weighted Portfolios

	Mean					Std. Dev.				
	Low	2	3	4	High	Low	2	3	4	High
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

Panel B: Equally-Weighted Portfolios

	Mean					Std. Dev.				
	Low	2	3	4	High	Low	2	3	4	High
Small	6.9	14.6	16.5	19.8	25.8	41.6	42.8	38.6	47.0	51.0
2	7.3	12.6	14.8	15.0	15.6	35.2	34.0	33.3	35.1	35.1
3	7.9	11.4	12.7	13.1	15.1	30.0	29.3	27.6	28.0	32.4
4	7.9	9.2	10.9	12.2	13.5	24.6	26.1	27.2	28.2	36.6
Big	6.6	8.2	9.1	9.7	10.8	21.3	20.4	24.1	27.0	32.9

Table 3: CDRM: Time-Series and Cross-Sectional Regression Results - Value-Weighted Portfolios

Panel A reports the beta estimates that result from time-series regressions of excess returns on the CDRM risk factors. Test assets are the 25 value-weighted portfolios sorted by size (vertical) and book-to-market value (horizontal). The sample period is 1927-2008, and the sampling frequency is annual. The t-statistics are formulated for the null hypothesis that the true parameter is zero. The table also displays the R^2 of each time-series regression. Panel B reports the estimated λ from a cross-sectional regression of average excess returns on estimated betas. For details on statistical inference, see the Appendix.

Panel A: Time-Series Regressions

	Low	2	3	4	High	Low	2	3	4	High
			$\hat{\beta}_W$					t_W		
Small	1.428	1.394	1.359	1.412	1.539	10.16	12.69	14.29	9.34	9.86
2	1.314	1.306	1.235	1.317	1.327	13.38	11.14	11.67	10.69	11.88
3	1.283	1.175	1.131	1.151	1.248	10.79	13.45	14.81	16.50	10.70
4	1.064	1.079	1.136	1.122	1.374	20.50	11.66	14.40	14.18	9.10
Big	0.969	0.898	0.965	1.068	1.286	26.03	36.66	14.83	12.86	10.55
			$\hat{\beta}_N$					t_N		
Small	-0.187	-0.270	-0.329	-0.426	-0.461	-1.27	-1.90	-2.48	-2.67	-2.47
2	-0.170	-0.216	-0.296	-0.291	-0.295	-1.34	-1.91	-2.42	-2.05	-2.07
3	-0.073	-0.228	-0.212	-0.292	-0.267	-0.69	-2.26	-1.94	-2.54	-1.84
4	0.070	-0.137	-0.164	-0.261	-0.153	1.07	-1.73	-1.66	-2.72	-1.10
Big	0.138	-0.044	-0.049	-0.105	-0.141	1.86	-0.92	-0.72	-1.26	-1.40
			R^2							
Small	61.1	69.2	71.4	67.0	67.1					
2	72.7	76.3	74.5	72.6	71.6					
3	76.3	80.9	79.1	78.0	67.7					
4	83.7	79.2	81.8	75.8	69.3					
Big	87.2	91.6	82.2	78.5	71.3					

Panel B: Cross-Sectional Regression

$\hat{\lambda}_W$	0.066	t_W	2.84
$\hat{\lambda}_N$	-0.148	t_N	-2.36

Table 4: CDRM: Time-Series and Cross-Sectional Regression Results - Equally-Weighted Portfolios

Panel A reports the beta estimates that result from time-series regressions of excess returns on the CDRM risk factors. Test assets are the 25 equally-weighted portfolios sorted by size (vertical) and book-to-market value (horizontal). The sample period is 1927-2008, and the sampling frequency is annual. The t-statistics are formulated for the null hypothesis that the true parameter is zero. The table also displays the R^2 of each time-series regression. Panel B reports the estimated λ from a cross-sectional regression of average excess returns on estimated betas. For details on statistical inference, see the Appendix.

Panel A: Time-Series Regressions

	Low	2	3	4	High	Low	2	3	4	High
			$\hat{\beta}_W$					t_W		
Small	1.498	1.671	1.451	1.625	1.740	10.79	12.35	11.56	5.78	6.48
2	1.388	1.363	1.310	1.371	1.363	10.39	8.65	8.81	8.40	9.67
3	1.259	1.214	1.165	1.158	1.261	12.16	10.77	13.89	15.80	10.76
4	1.085	1.104	1.172	1.165	1.456	19.23	11.51	13.66	14.26	8.46
Big	0.981	0.931	1.069	1.133	1.277	31.19	24.98	19.03	11.58	9.74
			$\hat{\beta}_N$					t_N		
Small	-0.237	-0.338	-0.405	-0.522	-0.603	-1.36	-1.97	-2.69	-2.43	-2.40
2	-0.250	-0.249	-0.336	-0.335	-0.305	-1.90	-2.02	-2.49	-2.24	-2.04
3	-0.067	-0.249	-0.219	-0.283	-0.288	-0.63	-2.26	-2.10	-2.51	-1.99
4	0.055	-0.144	-0.176	-0.277	-0.164	0.83	-1.76	-1.84	-2.78	-1.14
Big	0.125	-0.077	-0.128	-0.106	-0.178	2.70	-1.63	-1.68	-1.15	-1.69
			R^2							
Small	57.3	68.0	64.5	55.3	54.1					
2	68.9	71.2	69.8	68.9	67.5					
3	76.0	76.7	79.0	76.9	68.0					
4	83.7	78.5	81.7	76.9	69.1					
Big	90.9	90.4	86.4	76.7	66.2					

Panel B: Cross-Sectional Regression

$\hat{\lambda}_W$	0.061	t_W	2.52
$\hat{\lambda}_N$	-0.187	t_N	-2.90

Table 5: CDRM: Risk Compensations

The table shows estimated expected excess return compensations (percentage) that are associated with market risk ($\hat{\beta}_W \cdot \hat{\lambda}_W$) and creative destruction risk ($\hat{\beta}_N \cdot \hat{\lambda}_N$). Test assets are the 25 portfolios sorted by size (vertical) and book-to-market value (horizontal). The sample period is 1927-2008, and the sampling frequency is annual. Panel A shows the results for value-weighted Fama-French portfolios; Panel B shows the results for equally-weighted Fama-French portfolios. The delta method is used to compute the t-statistic for a test that the respective risk compensation is zero. For details on statistical inference, see the Appendix.

Panel A: Value-Weighted Portfolios

	Low	2	3	4	High	Low	2	3	4	High
			$\hat{\beta}_W \cdot \hat{\lambda}_W \times 100$					t_W		
Small	9.4	9.2	9.0	9.3	10.2	2.76	2.70	2.73	2.56	2.57
2	8.7	8.6	8.2	8.7	8.8	2.67	2.59	2.63	2.59	2.66
3	8.5	7.8	7.5	7.6	8.2	2.62	2.69	2.66	2.72	2.64
4	7.0	7.1	7.5	7.4	9.1	2.75	2.64	2.68	2.72	2.55
Big	6.4	5.9	6.4	7.1	8.5	2.79	2.82	2.75	2.72	2.80
			$\hat{\beta}_N \cdot \hat{\lambda}_N \times 100$					t_N		
Small	2.8	4.0	4.9	6.3	6.8	1.20	2.02	2.59	2.87	2.81
2	2.5	3.2	4.4	4.3	4.4	1.38	2.13	2.84	2.55	2.60
3	1.1	3.4	3.1	4.3	3.9	0.73	2.45	2.55	2.88	2.20
4	-1.0	2.0	2.4	3.9	2.3	-0.93	1.85	1.96	2.72	1.25
Big	-2.0	0.6	0.7	1.5	2.1	-1.81	0.87	0.76	1.30	1.34

Panel B: Equally-Weighted Portfolios

	Low	2	3	4	High	Low	2	3	4	High
			$\hat{\beta}_W \cdot \hat{\lambda}_W \times 100$					t_W		
Small	9.2	10.2	8.9	10.0	10.7	2.43	2.35	2.38	2.14	2.17
2	8.5	8.4	8.0	8.4	8.4	2.32	2.26	2.29	2.26	2.33
3	7.7	7.4	7.1	7.1	7.7	2.38	2.36	2.37	2.42	2.37
4	6.7	6.8	7.2	7.1	8.9	2.43	2.37	2.39	2.43	2.27
Big	6.0	5.7	6.6	6.9	7.8	2.49	2.49	2.46	2.42	2.47
			$\hat{\beta}_N \cdot \hat{\lambda}_N \times 100$					t_N		
Small	4.4	6.3	7.6	9.8	11.3	1.27	2.34	3.39	3.23	3.42
2	4.7	4.7	6.3	6.3	5.7	2.09	2.46	3.45	3.24	2.97
3	1.3	4.7	4.1	5.3	5.4	0.68	2.77	2.85	3.21	2.64
4	-1.0	2.7	3.3	5.2	3.1	-0.76	2.03	2.19	3.33	1.35
Big	-2.3	1.5	2.4	2.0	3.3	-2.37	1.64	1.94	1.29	1.76

Table 6: Model Comparison: CAPM, Fama-French, and CDRM

The table reports the λ estimates for CAPM, Fama-French model, and CDRM. Test assets are the 25 size and book-to-market sorted portfolios, and the sample period is 1927-2008 at annual frequency. The t-statistics (in parentheses) are formulated for the null hypothesis that the true parameter is zero. The table also reports the p-values of the first-stage GMM J-statistics and the cross-sectional R^2, both in percentages. The cross-sectional R^2 come from a regression of average realized excess returns on betas and a constant

Panel A: Value-Weighted Portfolios

	$\hat{\lambda}_W$	$\hat{\lambda}_{HML}$	$\hat{\lambda}_{SMB}$	$\hat{\lambda}_N$	p-val.	R^2
CAPM	0.090				0.3	24.1
	(3.91)					
Fama-French	0.068	0.060	0.035		2.6	70.5
	(2.89)	(3.73)	(2.04)			
CDRM	0.066			-0.148	1.4	51.3
	(2.84)			(-2.36)		

Panel B: Equally-Weighted Portfolios

	$\hat{\lambda}_W$	$\hat{\lambda}_{HML}$	$\hat{\lambda}_{SMB}$	$\hat{\lambda}_N$	p-val.	R^2
CAPM	0.096				0.5	49.4
	(4.21)					
Fama-French	0.061	0.066	0.049		2.2	83.4
	(2.45)	(4.05)	(3.28)			
CDRM	0.061			-0.187	3.2	73.1
	(2.52)			(-2.90)		

Table 7: Weights of the Invention-Mimicking Portfolio

The table shows the results of a time-series regression, $pg_t = \gamma_0 + \sum_{i=1}^{6} \gamma_i r^e_{B,i,t} + v_t$, used to estimate the weights of the invention-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 and French, 1993)). The sample period is 1927-2008, at annual frequency. Coefficient estimates are reported on the left-hand side. The t-statistics (right-hand side) are formulated for the null hypothesis that the true parameter is zero. The table also displays the R^2 and p-value of a Wald test of the null hypothesis that $\gamma_1 = \gamma_2 = ... = \gamma_6 = 0$.

Portfolio Weights						t			
	Growth	Neutral	Value	Sum			Growth	Neutral	Value
Small	0.098	-0.244	-0.090	-0.236		Small	1.14	-1.31	-0.63
Big	0.243	-0.099	0.092	0.236		Big	2.01	-0.44	0.54
Sum	0.341	-0.343	0.002						
						R^2 (%)		10.3	
						p-val.(%)		1.5	

Table 8: Invention-Mimicking Portfolio: Descriptive Statistics

The table reports descriptive statistics for the invention-mimicking portfolio. It shows the portfolio's mean excess return, its standard deviation, and its correlation with the market excess return (r^e_W), and the Fama-French factors *HML* and *SMB*. The sample period is 1927-2008, at annual frequency.

Mean×100		-1.7
Std. Dev.×100		4.4
Correlation with:	r^e_W	-0.21
	HML	-0.67
	SMB	-0.66

Table 9: Mimicking Portfolio CDRM: Time-Series and Cross-Sectional Regression Results - Value-Weighted Portfolios

Panel A reports the beta estimates that result from time-series regressions of the test assets' excess returns on the invention-mimicking portfolio's excess return, r_M^e, and the return of the wealth portfolio proxy, r_W. Test assets are the 25 value-weighted Fama-French portfolios sorted by size (vertical) and book-to-market value (horizontal). The sample period is 1927-2008, and the sampling frequency is annual. The t-statistics are formulated for the null hypothesis that the true parameter is zero. Panel A also displays the R^2 of each time-series regression. Panel B reports the estimated λ from a cross-sectional regression of average excess returns on the estimated betas, as well as $\Delta\hat{\lambda} = \hat{\lambda}_{cs} - \hat{\lambda}_{ts}$, and the associated p-value of a test that $\Delta\hat{\lambda}$ is significantly different from zero. Statistical inference takes into account that the parameters are estimated via three subsequent regressions that yield the mimicking portfolio weights, the beta estimates, and the lambda estimates. For details on statistical inference, see the Appendix.

Panel A: Time-Series Regressions

	Low	2	3	4	High	Low	2	3	4	High
			$\hat{\beta}_W$					t_W		
Small	1.391	1.306	1.236	1.256	1.371	9.17	8.03	6.47	5.48	5.57
2	1.268	1.218	1.124	1.186	1.203	10.34	8.25	7.01	6.26	6.04
3	1.265	1.105	1.046	1.053	1.125	11.66	9.78	8.75	7.68	5.64
4	1.082	1.028	1.066	1.043	1.286	17.08	10.16	10.35	7.86	7.32
Big	1.018	0.899	0.933	1.026	1.233	14.29	33.51	14.71	11.73	8.76
			$\hat{\beta}_M$					t_M		
Small	-1.021	-2.230	-3.110	-3.937	-4.232	-0.93	-2.13	-2.83	-2.86	-2.88
2	-1.210	-2.198	-2.791	-3.236	-3.086	-1.44	-2.55	-3.01	-2.92	-2.54
3	-0.474	-1.816	-2.137	-2.501	-3.040	-0.54	-2.63	-3.10	-2.95	-2.39
4	0.472	-1.279	-1.740	-2.042	-2.136	0.75	-1.94	-2.57	-2.25	-1.71
Big	1.249	-0.027	-0.775	-1.064	-1.318	3.12	-0.11	-1.34	-1.41	-1.16
			R^2							
Small	62.0	75.5	85.1	85.6	85.2					
2	74.8	84.5	88.5	89.3	86.2					
3	76.7	87.7	89.7	91.0	83.1					
4	84.2	83.4	89.2	84.5	76.1					
Big	92.7	91.5	84.4	81.5	74.1					

Panel B: Cross-Sectional and Time-Series λ

$\hat{\lambda}_W$	0.061	t_W	2.60
$\hat{\lambda}_M^{cs}$	-0.021	t_M^{cs}	-2.80
$\hat{\lambda}_M^{ts}$	-0.017	t_M^{ts}	-1.85
$\Delta\hat{\lambda}$	-0.005	p-val. (%)	56.1

Table 10: Mimicking Portfolio CDRM: Time-Series and Cross-Sectional Regression Results - Equally-Weighted Portfolios

Panel A reports the beta estimates that result from time-series regressions of the test assets' excess returns on the invention-mimicking portfolio's excess return, r_M^e, and the return of the wealth portfolio proxy, r_W. Test assets are the 25 equally-weighted Fama-French portfolios sorted by size (vertical) and book-to-market value (horizontal). The sample period is 1927-2008, and the sampling frequency is annual. The t-statistics are formulated for the null hypothesis that the true parameter is zero. Panel A also displays the R^2 of each time-series regression. Panel B reports the estimated λ from a cross-sectional regression of average excess returns on the estimated betas, as well as $\Delta\hat{\lambda} = \hat{\lambda}_{cs} - \hat{\lambda}_{ts}$, and the associated p-value of a test that $\Delta\hat{\lambda}$ is significantly different from zero. Statistical inference takes into account that the parameters are estimated via three subsequent regressions that yield the mimicking portfolio weights, the beta estimates, and the lambda estimates. For details on statistical inference, see the Appendix.

Panel A: Time-Series Regressions

	Low	2	3	4	High	Low	2	3	4	High
			$\hat{\beta}_W$					t_W		
Small	1.430	1.575	1.312	1.437	1.531	8.20	8.14	5.87	4.47	4.45
2	1.322	1.263	1.188	1.230	1.226	8.42	7.02	6.23	5.67	5.43
3	1.234	1.132	1.075	1.056	1.135	12.06	8.31	8.38	7.32	5.66
4	1.094	1.048	1.099	1.082	1.365	17.63	9.64	9.91	7.86	7.25
Big	1.014	0.913	1.017	1.068	1.214	20.52	21.82	14.24	9.37	7.78
			$\hat{\beta}_M$					t_M		
Small	-1.766	-2.489	-3.531	-4.750	-5.298	-1.34	-2.07	-2.66	-2.47	-2.64
2	-1.737	-2.504	-3.079	-3.495	-3.372	-1.65	-2.34	-2.78	-2.80	-2.52
3	-0.626	-2.086	-2.248	-2.574	-3.115	-0.74	-2.49	-3.00	-2.92	-2.40
4	0.253	-1.397	-1.818	-2.153	-2.208	0.43	-2.03	-2.56	-2.43	-1.70
Big	0.882	-0.473	-1.285	-1.573	-1.582	3.00	-1.58	-2.40	-1.81	-1.31
			R^2							
Small	60.0	73.1	78.0	72.0	71.5					
2	72.5	80.3	83.7	85.7	83.3					
3	76.7	84.8	90.2	90.6	83.7					
4	83.8	83.3	89.2	85.9	75.5					
Big	93.5	91.1	91.2	82.7	69.9					

Panel B: Cross-Sectional and Time-Series λ

$\hat{\lambda}_W$	0.055	t_W	2.19
$\hat{\lambda}_M^{cs}$	-0.026	t_M^{cs}	-2.86
$\hat{\lambda}_M^{ts}$	-0.017	t_M^{ts}	-1.85
$\Delta\hat{\lambda}$	-0.010	p-val. (%)	33.5

Table 11: Mimicking Portfolio CDRM: Risk Compensations

The table reports estimated expected excess return compensations (percentage) that are implied by the mimicking portfolio version of the CDRM. Test assets are the 25 portfolios sorted by size (vertical) and book-to-market value (horizontal). The sample period is 1927-2008, and the sampling frequency is annual. Panel A shows the results for value-weighted Fama-French portfolios; Panel B shows the results for equally-weighted Fama-French portfolios. The delta method is used to compute the t-statistic for a test that the respective risk-compensation is zero. Statistical inference takes into account that the parameters are obtained by three subsequent regressions that yield the mimicking portfolio weights, the beta estimates, and the lambda estimates. For details on statistical inference, see the Appendix.

Panel A: Value-Weighted Portfolios

	Low	2	3	4	High	Low	2	3	4	High
		$\hat{\beta}_W \cdot \hat{\lambda}_W \times 100$						t_W		
Small	8.5	8.0	7.6	7.7	8.4	2.52	2.44	2.46	2.31	2.33
2	7.7	7.4	6.9	7.3	7.4	2.46	2.39	2.42	2.37	2.41
3	7.7	6.8	6.4	6.4	6.9	2.42	2.49	2.45	2.47	2.37
4	6.6	6.3	6.5	6.4	7.9	2.47	2.42	2.48	2.49	2.37
Big	6.2	5.5	5.7	6.3	7.5	2.50	2.56	2.53	2.53	2.62
		$\hat{\beta}_M \cdot \hat{\lambda}_M \times 100$						t_M		
Small	2.2	4.7	6.6	8.4	9.0	0.89	2.06	2.67	2.75	2.81
2	2.6	4.7	5.9	6.9	6.6	1.30	2.30	2.87	2.94	2.79
3	1.0	3.9	4.5	5.3	6.5	0.52	2.41	2.99	3.11	2.63
4	-1.0	2.7	3.7	4.3	4.5	-0.81	1.83	2.78	2.54	1.92
Big	-2.7	0.1	1.6	2.3	2.8	-2.90	0.11	1.30	1.58	1.30

Panel B: Equally-Weighted Portfolios

	Low	2	3	4	High	Low	2	3	4	High
		$\hat{\beta}_W \cdot \hat{\lambda}_W \times 100$						t_W		
Small	7.8	8.6	7.2	7.8	8.3	2.10	2.04	2.05	1.90	1.91
2	7.2	6.9	6.5	6.7	6.7	2.04	2.00	2.02	2.00	2.04
3	6.7	6.2	5.9	5.8	6.2	2.08	2.07	2.09	2.11	2.07
4	6.0	5.7	6.0	5.9	7.4	2.09	2.07	2.10	2.13	2.04
Big	5.5	5.0	5.5	5.8	6.6	2.13	2.16	2.17	2.15	2.20
		$\hat{\beta}_M \cdot \hat{\lambda}_M \times 100$						t_M		
Small	4.6	6.5	9.2	12.4	13.8	1.30	2.17	3.11	3.00	3.28
2	4.5	6.5	8.0	9.1	8.8	1.67	2.58	3.35	3.66	3.64
3	1.6	5.5	5.9	6.7	8.1	0.73	2.68	3.45	3.87	3.31
4	-0.7	3.7	4.8	5.6	5.8	-0.44	2.17	3.24	3.26	2.20
Big	-2.3	1.2	3.4	4.1	4.1	-3.34	1.53	2.42	2.29	1.52

Table 12: Mimicking Portfolio CDRM: Time-Series and Cross-Sectional Regression Results - Value-Weighted Portfolios, Quarterly Postwar Data

Panel A reports the beta estimates that result from time-series regressions of excess returns on the CDRM risk factors using the invention-mimicking portfolio instead of patenting activity. Test assets are the 25 value-weighted portfolios sorted by size (vertical) and book-to-market value (horizontal). The sample period is 1950:Q1-2008:Q4, and the sampling frequency is quarterly. The t-statistics are formulated for the null hypothesis that the true parameter is zero. Panel A also displays the R^2 of each time-series regression. Panel B reports the estimated λ from a cross-sectional regression of average excess returns on the estimated betas, as well as $\Delta\hat{\lambda} = \hat{\lambda}_{cs} - \hat{\lambda}_{ts}$, and the associated p-value of a test that $\Delta\hat{\lambda}$ is significantly different from zero. Statistical inference takes into account that the parameters are obtained by three subsequent regressions that yield the mimicking portfolio weights, the beta estimates, and the lambda estimates. For details on statistical inference, see the Appendix.

Panel A: Time-Series Regressions

	Low	2	3	4	High	Low	2	3	4	High
			$\hat{\beta}_W$					t_W		
Small	1.422	1.190	0.985	0.921	0.973	7.22	5.32	4.47	4.09	3.63
2	1.384	1.100	0.943	0.894	0.930	10.30	6.31	5.04	4.51	4.07
3	1.335	1.030	0.881	0.855	0.847	16.38	8.30	5.53	4.69	3.92
4	1.275	0.993	0.910	0.873	0.921	18.71	9.65	6.95	6.18	4.30
Big	1.108	0.913	0.776	0.761	0.802	10.39	23.65	11.78	6.58	5.64
			$\hat{\beta}_M$					t_M		
Small	-1.582	-2.122	-2.197	-2.242	-2.720	-1.11	-1.84	-2.12	-2.16	-2.20
2	-1.013	-1.720	-1.843	-2.044	-2.336	-0.93	-2.11	-2.53	-2.47	-2.23
3	-0.272	-1.266	-1.631	-1.848	-2.173	-0.32	-2.42	-2.82	-2.66	-2.24
4	0.136	-0.978	-1.287	-1.433	-2.043	0.22	-2.41	-2.62	-2.45	-2.30
Big	1.113	0.003	-0.427	-0.983	-1.147	2.76	0.01	-0.83	-1.42	-1.17
			R^2							
Small	71.2	81.0	82.4	82.6	82.4					
2	80.1	87.1	90.6	89.3	84.0					
3	82.9	90.2	91.1	90.2	81.0					
4	87.0	89.3	90.7	88.4	85.5					
Big	95.8	88.0	79.1	81.5	72.9					

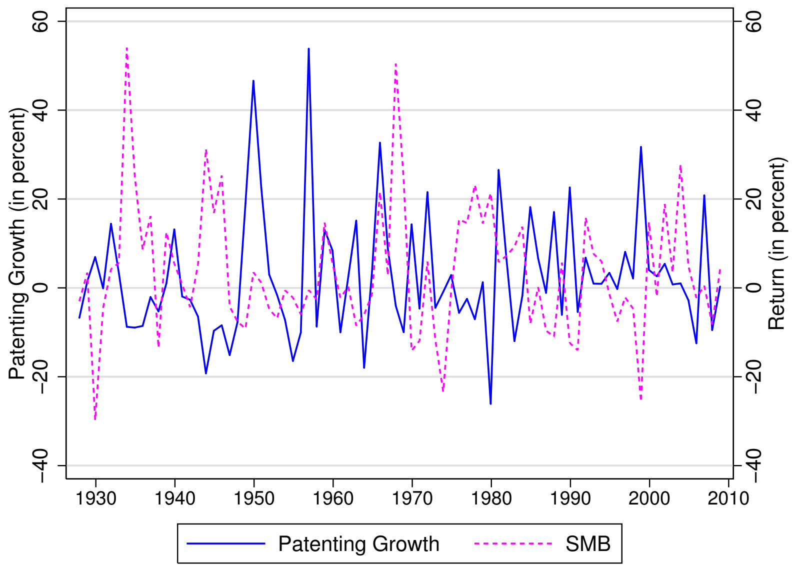
Panel B: Cross-Sectional and Time-Series λ

$\hat{\lambda}_W$	0.013	t_W	2.09
$\hat{\lambda}_M^{cs}$	-0.007	t_M^{cs}	-2.30
$\hat{\lambda}_M^{ts}$	-0.005	t_M^{ts}	5.43
$\Delta\hat{\lambda}$	-0.003	p-val. (%)	58.5

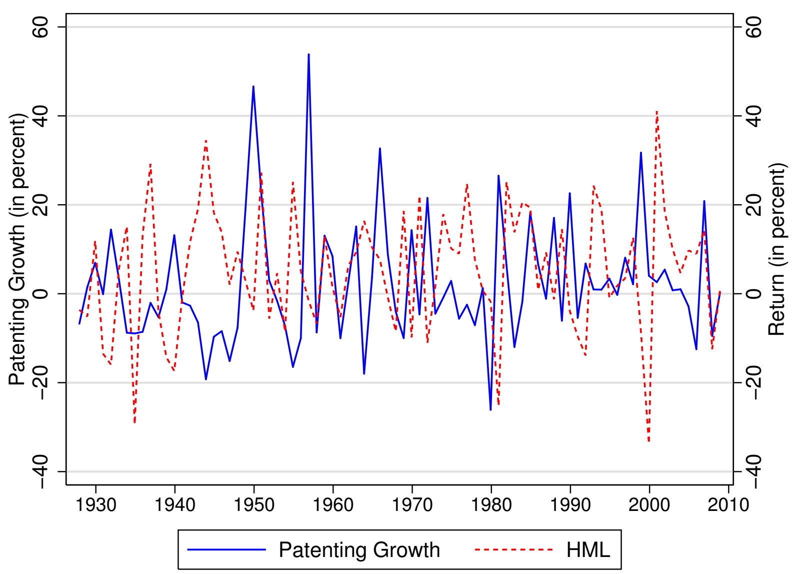
Table 13: Mimicking Portfolio CDRM: Risk Compensations - Value-Weighted Portfolios, Quarterly Postwar Data

The table reports estimated expected excess return compensations (percentage) that are implied by the mimicking portfolio version of the CDRM. Test assets are the 25 value-weighted portfolios sorted by size (vertical) and book-to-market value (horizontal). The sample period is 1950:Q1-2008:Q4, and the sampling frequency is quarterly. The delta method is used to compute the t-statistic for a test that the respective risk compensation is zero. Statistical inference takes into account that the parameters are obtained by three subsequent regressions that yield the mimicking portfolio weights, the beta estimates, and the lambda estimates. For details on statistical inference, see the Appendix.

	Low	2	3	4	High	Low	2	3	4	High
			$\hat{\beta}_W \cdot \hat{\lambda}_W \times 100$					t_W		
Small	1.8	1.5	1.2	1.2	1.2	1.91	1.89	1.89	1.89	1.87
2	1.7	1.4	1.2	1.1	1.2	1.96	1.96	1.97	1.98	1.95
3	1.7	1.3	1.1	1.1	1.1	1.99	2.03	2.04	2.01	1.94
4	1.6	1.3	1.1	1.1	1.2	1.99	2.08	2.07	2.06	1.95
Big	1.4	1.2	1.0	1.0	1.0	2.03	2.10	2.13	2.11	2.08
			$\hat{\beta}_M \cdot \hat{\lambda}_M \times 100$					t_M		
Small	1.2	1.6	1.6	1.7	2.0	1.07	1.81	2.28	2.53	2.84
2	0.8	1.3	1.4	1.5	1.7	0.87	2.01	2.66	3.26	3.09
3	0.2	0.9	1.2	1.4	1.6	0.32	2.26	3.18	3.26	3.05
4	-0.1	0.7	1.0	1.1	1.5	-0.22	2.32	2.88	2.97	2.53
Big	-0.8	0.0	0.3	0.7	0.9	-2.63	-0.01	0.84	1.48	1.18



Panel A: Patenting Growth and *SMB*



Panel B: Patenting Growth and *HML*

Figure 1: Patenting Growth and Fama-French Factors
The graph shows patent growth (percentage) and the Fama-French factors (*SMB*) and (*HML*) over the period 1927-2008.

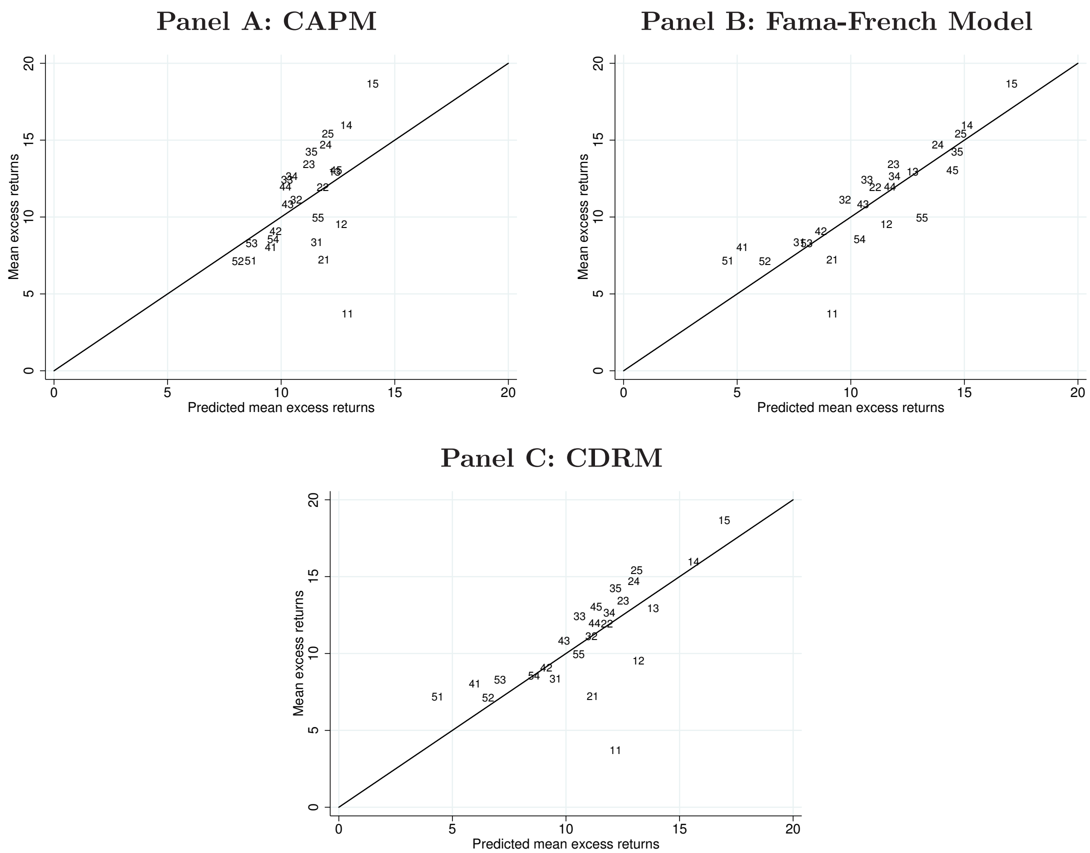
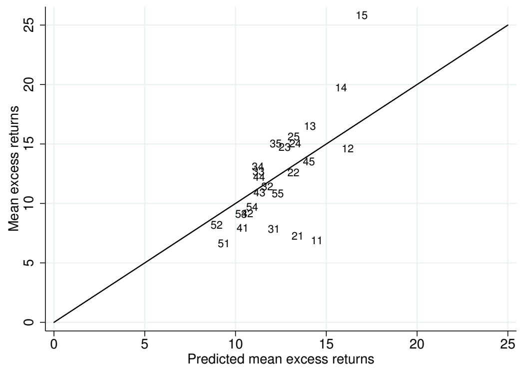


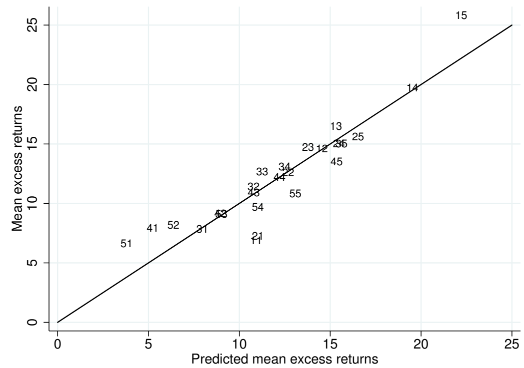
Figure 2: Predicted vs. Actual Mean Excess Returns - Value-Weighted Portfolios

The figures compare predicted vs. realized average excess returns (percentage) given by the CAPM (Panel A), the Fama-French model (Panel B), and the CDRM (Panel C). The sample period is 1927-2008; the sampling frequency is annual. The test assets are the value-weighted 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 refers to the book-to-market quintile (1 being the lowest and 5 the highest).

Panel A: CAPM



Panel B: Fama-French Model



Panel C: CDRM

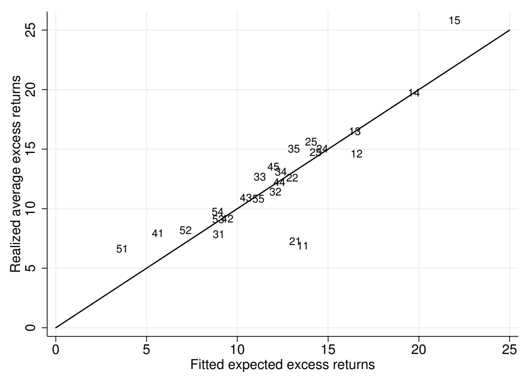


Figure 3: Predicted vs. Actual Mean Excess Returns - Equally-Weighted Portfolios

The figures compare predicted vs. realized average excess returns (percentage) given by the CAPM (Panel A), the Fama-French model (Panel B), and the CDRM (Panel C). The sample period is 1927-2008; the sampling frequency is annual. The test assets are the equally-weighted 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 indicates the book-to-market quintile (1 being the lowest and 5 the highest).

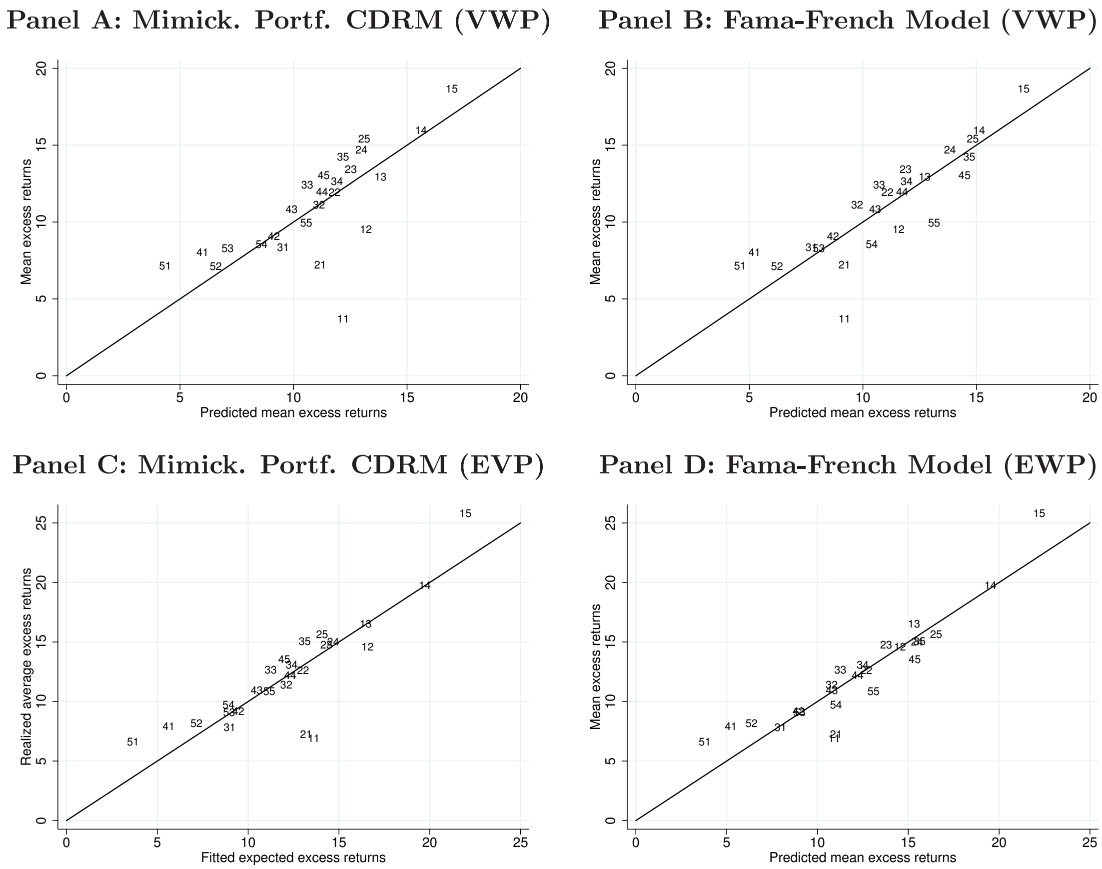


Figure 4: Predicted vs. Actual Mean Excess Returns - Mimicking Portfolio CDRM vs. Fama-French Model

The figures compare predicted vs. realized average excess returns (percentage) given by the Invention Mimicking CDRM and Fama-French model. The sample period is 1927-2008; the sampling frequency is annual. 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 indicates the book-to-market quintile (1 being the lowest and 5 the highest). Panels A and B show the results for value-weighted portfolios (VWP), and Panels C and D show the results for equally-weighted portfolios (EWP). The cross-sectional R^2 (unadjusted) are, for EVPs, 81.1% (Mimicking Portfolio CDRM) vs. 83.4% (Fama-French model), and for VWPs, 65.4% (Mimicking Portfolio CDRM) vs. 70.5% (Fama-French model).