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Creative Destruction and Asset Prices

Joachim Grammig and Stephan Jank*

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 must offer higher expected returns to compensate for the risk posed by serendipitous invention activity, whereas large-growth stocks provide protection against creative destruction and receive expected return discounts. A 2-factor model that accounts for creative-destruction risk effectively explains the cross-sectional return variation of size- and book-to-market-sorted portfolios. The estimated risk compensations associated with creative destruction are substantial and statistically significant, indicating their relevance for asset pricing.

I. Introduction

Small stocks have earned higher average returns than large stocks, and stocks with high book-to-market ratios (value stocks) have yielded higher average returns than growth stocks, which have low book-to-market ratios. However, these traits are not captured sufficiently in empirical implementations of the static capital asset pricing model (CAPM). Fama and French's (1993) 3-factor model accounts for size and value premia, but it leaves the identity of the fundamental risk represented by the Fama–French factors uncertain.

By linking Schumpeter's notion of creative destruction to asset pricing, the present study seeks to test a novel explanation of size and value premia. Specif-

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ically, we argue that serendipitous invention activity can render business models and human capital linked to current technology obsolete. This process creates a risk that is reflected in sizable expected return compensations.

The "process of industrial mutation [. . .] incessantly revolutionizes the economic structure from within, incessantly destroying the old one, incessantly creating a new one" (Schumpeter (1961), p. 83), and it occurs throughout history. Means of transportation, for example, developed within only a century, from horse carriages to railroad, then to automobiles and airplanes. Recent inventions in the field of information technology have challenged traditional business models in the music, media, and newspaper industries. Inventions are pivotal for economic growth, but they also represent a threat to existing firms, their investors, and the workforce.

In this study, we motivate and empirically test a 2-factor asset pricing model that 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 book-to-market-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 an additional 7 percentage points of expected return will be required each year to compensate for creative-destruction risk. Using an invention-mimicking portfolio as an alternative risk factor proxy accentuates these results. Previous research concurs that small-value firms are under distress, in that they are less productive and have a higher default probability (Chan and Chen (1991), Fama and French (1995), Vassalou and Xing (2004), and 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 2 percentage points for the large-growth portfolio.

Despite its parsimonious parametrization, the CDRM achieves a good cross-sectional goodness of fit with size- and book-to-market-sorted portfolios. The model passes various plausibility and model specification tests. Specifically, all empirical results remain robust, and even improve, when we include industry portfolios as test assets. Moreover, the 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, Nagel, and Shanken (2010)). We augment the inference based on the generalized method of moments (GMM) with bootstrap simulations along the lines of Maio and Santa-Clara (2013) to assess the statistical significance of the cross-sectional goodness-of-fit measures and the estimates of the risk prices. Furthermore, the CDRM performs favorably when we apply the requirements for logical consistency with the intertemporal capital asset pricing model (ICAPM) put forth by Maio and Santa-Clara (2012): The point estimate of the coefficient of relative risk aversion is economically reasonable, and the estimated intertemporal risk price associated with invention activity has the theory-implied negative sign. For the main analysis, we adopt a long-run perspective using annual data from 1927–2008. The conclusions remain unchanged when we use postwar data sampled at quarterly frequency instead.

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Our study connects several strands of literature. First, it bridges creative destruction, a familiar notion in economic growth theory (e.g., Segerstrom, Anant, and Dinopoulos (1990), Aghion and Howitt (1992), and Helpman and Trajtenberg (1994)), and asset pricing. Accordingly, we contribute to literature that investigates the effects of technological innovations on asset prices (Nicholas (2008), Hsu (2009), Comin, Gertler, and Santacreu (2009), Pástor and Veronesi (2009), and Gârleanu, Panageas, and Yu (2012)). In a related study, Gârleanu, Kogan, and Panageas (2012) propose an overlapping-generations model in which innovation erodes the human capital of older workers, thus creating a displacement risk factor. Because the rents of technological innovations are earned by future cohorts of investors, the present generation cannot use financial markets to avoid the displacement effect. Second, we incorporate creative-destruction risk into the ICAPM framework 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 and Vuolteenaho (2004), Brennan, Wang, and Xia (2004), Petkova (2006), and Koijen, Lustig, and Van Nieuwerburgh (2012)). Third, our study complements literature that aims to explain the value premium. For example, in the Zhang (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. Lioui and Maio (2014) show that value stocks have a greater interest rate risk, which is a priced factor in their ICAPM variant. Fourth, we extend studies that associate size and book-to-market ratios with firm-specific measures of distress (e.g., Chan, Chen, and Hsieh (1985), Chan and Chen (1991), and Fama and French (1995)) by proposing a connection to an aggregate distress factor.

The remainder of this paper is organized as follows: In Section II, we introduce the theoretical motivation that relates invention activity to asset prices. Section III contains a description of the data, and we motivate our choice of the risk factor proxies. We outline our econometric methodology in Section IV. The results of the main empirical analysis are presented in Section V, for which we adopt a long-run perspective using annual data. In Section VI, we test our model using industry portfolios and quarterly postwar data. We discuss the logical consistency of our findings with the theoretical motivation in Section VII, and then conclude in Section VIII.

II. Theoretical Motivation

Our theoretical framework links Schumpeter's notion of creative destruction to asset pricing. It embodies the idea that certain inventions may turn into what Schumpeterian growth theory refers to as general purpose technologies (GPTs), a term that acknowledges their pervasive impact across a wide range of sectors (see Helpman and Trajtenberg (1994)). Although GPTs foster long-run economic growth, they also render established technologies and human capital obsolete and thus represent a latent threat to the future financial and nonfinancial wealth of the current cohort of investors. How do they account for the ambivalent nature of inventions, and what are the implications for asset pricing? We address this

question within Merton's (1973) ICAPM framework, in which we use invention activity as a state variable, drawing on the general equilibrium model of Gârleanu, Kogan, and Panageas (2012).

As pointed out by Maio and Santa-Clara (2012), an ICAPM state variable needs to forecast changes in investment opportunities. The covariation of an asset's return with innovations of the state variable then determines whether the respective asset can provide a hedge against intertemporal (reinvestment) risk or, rather, accentuates it. The overlapping-generations model by Gârleanu, Kogan, and Panageas (2012) suggests that invention activity qualifies as such a state variable. The authors argue that the economic rents of current inventions get pocketed by future cohorts of investors, through new businesses that are created when serendipitous invention activity turns into product and process innovations. In contrast, the existing cohort of agents cannot make use of financial markets to avoid the downside of creative destruction, namely, that their human capital (in particular, that of older workers) may become redundant. Gârleanu, Kogan, and Panageas (2012) refer to this "dark side" of innovations as the *displacement effect*. Invention activity shocks thus lower the future value of financial wealth, insofar as this value stems from investments in extant businesses that may become imperiled by creative-destruction processes, and they potentially erode the future human capital of the current cohort of agents. When an invention shock occurs, it is not clear which business models and which workers' skills will become redundant because the invention has not yet turned into concrete product or process innovations. Yet the existing agents require a higher premium to hold stocks than could be inferred from aggregate consumption alone.

Gârleanu, Kogan, and Panageas (2012) also delineate an effect of invention activity on the cross section of asset returns. Extending their reasoning to the present context, we posit that innovative firms will derive a larger fraction of their value from inventions turning into GPTs and thus achieve higher valuation ratios ("growth" firms). When an invention shock occurs, the value of these firms further increases, and their returns contemporaneously covary positively with invention activity. When invention shocks predict negative returns to the financial and nonfinancial wealth of existing agents, growth firms provide, according to ICAPM logic, a hedge against these risks. As a result, growth firms will offer lower expected returns than less innovative firms, with their lower valuation ratios. The business models of these value firms are particularly endangered by shocks in invention activity, and their prices decrease when an invention activity shock occurs. In ICAPM terms, value firms are intertemporally risky assets: Their returns covary negatively with a state variable that predicts negative returns to the financial and nonfinancial capital of existing agents. Accordingly, they must offer higher expected returns.

To elaborate more formally, 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.[1] The agent consumes c_t of his wealth W_t and invests the remainder in a portfolio that yields a gross return $R_{W,t} = \sum_{i=1}^{n} w_{i,t} R_{i,t}$,

[1]The following exposition draws on Cochrane ((2005), ch. 9).

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where $R_{i,t}$ represents gross returns and $w_{i,t}$ represents 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 write the investor's maximization problem as

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

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

From the first-order conditions of equation (1), it follows that the stochastic discount factor (SDF) m_{t+1}, for which $\mathbb{E}_t[m_{t+1} R_{i,t+1}] = 1$, can be expressed as

$$m_{t+1} \quad = \quad \delta \frac{V_W(W_{t+1}, N_{t+1})}{V_W(W_t, N_t)}, \tag{2}$$

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:

$$\begin{aligned} \mathbb{E}_t[r^e_{i,t+1}] &= \mathrm{RRA}_t \mathrm{cov}_t \left[r^e_{i,t+1}, \frac{\Delta W_{t+1}}{W_t} \right] + \gamma_{N,t} \mathrm{cov}_t \left[r^e_{i,t+1}, \frac{\Delta N_{t+1}}{N_t} \right] \\ &= \gamma_t' \mathrm{cov}_t[f_{t+1}, r^e_{i,t+1}], \end{aligned} \tag{3}$$

where $r^e_{i,t+1} = R_{i,t+1} - R^f_{t+1}$, with R^f_{t+1} the gross risk-free rate,

$$\begin{aligned} \mathrm{RRA}_t &= -\frac{W_t V_{WW}(W_t, N_t)}{V_W(W_t, N_t)}, \\ \gamma_{N,t} &= -\frac{N_t V_{WN}(W_t, N_t)}{V_W(W_t, N_t)}, \end{aligned}$$

$f_{t+1} = (\Delta W_{t+1}/W_t, \Delta N_{t+1}/N_t)'$, and $\gamma_t = (\mathrm{RRA}_t, \gamma_{N,t})'$.[2]

Assuming time-invariant relative risk aversion (RRA) and prices of intertemporal (creative-destruction) risk (γ_N), an unconditional version of equation (3) reads as follows:[3]

$$\begin{aligned} \mathbb{E}[r^e_{i,t}] &= \mathrm{RRA}_t \times \mathrm{cov}\left[r^e_{i,t}, r_{W,t}\right] + \gamma_N \times \mathrm{cov}\left[r^e_{i,t}, \frac{\Delta N_t}{N_{t-1}} \right] \\ &= \gamma' \mathbb{E}[f^*_t r^e_{i,t}], \end{aligned} \tag{4}$$

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

[3] To obtain equation (4), we follow Maio and Santa-Clara (2012) and apply the law of total expectations to equation (3) and assume that $\mathrm{cov}\left(\mathbb{E}_t\left(r^e_{i,t+1}\right), \mathbb{E}_t\left(\Delta N_t / N_{t-1}\right)\right) \approx 0$ and $\mathrm{cov}\left(\mathbb{E}_t\left(r^e_{i,t+1}\right), \mathbb{E}_t\left(\Delta W_{t+1} / W_t\right)\right) \approx 0$. Unless the data are independent and identically distributed (iid), a conditional beta representation does not necessarily imply an unconditional counterpart. The conditions for its existence are outlined for the single-factor case by Singleton (2006) and Lewellen and Nagel (2006). Similar requirements can be stated for the 2-factor case. We assume that these conditions are fulfilled and base our econometric work on the unconditional beta representation in equation (5).

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where $f_t^* = f_t - \mathbb{E}(f_t)$, and γ_N is associated with the price of intertemporal risk. Using betas instead of covariances, we have:

$$\mathbb{E}[r_{i,t}^e] = \beta_{W,i}\lambda_W + \beta_{N,i}\lambda_N = \beta_i'\lambda, \tag{5}$$

where $\beta_i = (\beta_{W,i}, \beta_{N,i})' = \mathbb{E}(f_t^* f_t^{*\prime})^{-1}\mathbb{E}(f_t^* r_{i,t}^e)$. Alternatively, we may write:

$$\mathbb{E}[(1 + b' f_t^*) r_{i,t}^e] = 0. \tag{6}$$

Equation (5) is the multiple-beta representation of a CDRM, equation (6) is its SDF representation, and equation (4) is its covariance representation. Their parameters are related as follows:

$$\begin{aligned} b &= \begin{bmatrix} b_W \\ b_N \end{bmatrix} = -\gamma = \begin{bmatrix} -\text{RRA} \\ -\gamma_N \end{bmatrix} \\ &= -\mathbb{E}(f_t^* f_t^{*\prime})^{-1} \begin{bmatrix} \lambda_W \\ \lambda_N \end{bmatrix} = -\mathbb{E}(f_t^* f_t^{*\prime})^{-1}\lambda. \end{aligned} \tag{7}$$

Moreover, $\lambda = -p(f^*) = \mathbb{E}[(1 + b' f_t^*) f_t^*]$ is associated with the prices of the risk factors (see Cochrane (1996)).

Extending the arguments posed by Maio and Santa-Clara (2012) to the present case, consistency with the ICAPM logic requires that $\gamma_N < 0$ and $\lambda_N < 0$. To see this, note that according to the previous reasoning, an increase in invention activity predicts negative returns to the financial wealth and human capital of the existing investor cohort. An intertemporally risky asset, one for which $\text{cov}[r_{i,t}^e, \Delta N_t / N_{t-1}] < 0$ and $\beta_{N,i} < 0$, must provide a higher expected excess return, whereas an asset for which $\text{cov}[r_{i,t}^e, \Delta N_t / N_{t-1}] > 0$ and $\beta_{N,i} > 0$ provides a hedge against the creative-destruction risk. Accordingly, ICAPM logic implies that $\gamma_N < 0$ and $\lambda_N < 0$.

III. Data and Descriptive Analysis

A. Proxies for Invention Activity and Test Assets

To conduct an empirical assessment of whether creative-destruction risk matters for asset pricing, we need a proxy for invention activity. R&D expenditures readily come to mind, but these data measure costs, not outcomes. Moreover, the efforts of R&D departments aim to protect and improve the firm's products, so they can gain or maintain a competitive edge. This is not the potentially destructive effect of undirected invention activity that we emphasize here, though.[4] Instead, we rely on 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

[4]Schumpeterian growth theory makes a distinction between innovations and inventions, which we adopt here. Innovations (inventions that have turned into new products or processes) may have a procyclical nature. Comin et al. (2009) relate the adoption of innovations to the business cycle, and Gârleanu, Panageas, and Yu (2012) consider a general equilibrium model that connects the adoption of technologies to asset prices. The focus of these papers is on the transfer of an invention to a product innovation, the technological cycle.

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patents. These data contain an entry for each patent issued at a specific date, spanning the period 1790–2008. Even though the USPTO data offer more detail (for recent periods), we compute the obvious proxy for invention activity, N_t, as the number of patents issued in period t. The net growth rate of patenting activity, denoted pg, then approximates $\Delta N/N$.

One could imagine a more sophisticated proxy for invention activity. For example, because certain inventions exert a greater future impact than others, we theoretically could try to filter out patents that emerged as significant ex post. Tracking subsequent patent citations is important for measuring the technological consequences of a specific invention (Nicholas (2008)). However, this issue loses some relevance when the goal is to account for creative-destruction risk in asset pricing. In hindsight, we could observe the success or failure of an invention and measure its subsequent impact, but instead, our focus is on the ex ante probability that an invention will destroy existing businesses. Because this is the actual threat that owners face, 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 (Townes (2003)); it exemplifies the far-reaching effects of an invention that were unforeseeable ex ante. Accordingly, we believe that the overall number of patents is a useful indicator to capture our notion of serendipitous invention activity.

Yet patents still represent an imperfect proxy for the kind of invention activity in which we are interested. A considerable share of patenting activity aims solely to preserve extant businesses and their products. Ideally, we would filter out protective patents so that we could focus on genuinely undirected, potentially destructive inventions. However, this intricate task would require assailable assumptions, which we chose to forgo. By using an unrefined proxy, we also avoid the danger of going fishing for a factor that proves to be ex post empirically significant. Moreover, the number of patents issued in a certain period can be influenced by other factors, such as the institutional settings of the patent office or backlogs in the patent-issuing process, which presumably would be aggravated at higher sampling frequencies.

To mitigate the problem of measurement errors in the patenting data, we also use the excess return of a factor-mimicking portfolio as an alternative risk proxy (Breeden, Gibbons, and Litzenberger (1989)). Similar to Vassalou (2003), we get the mimicking portfolio weights from a projection of patenting growth on the space spanned by the excess returns (returns less the risk-free rate proxy) of the six base assets used to construct the Fama and French (1993) factors HML (high minus low) and SMB (small minus big). This procedure entails estimating the following regression equation:

$$pg_t = \psi_0 + \sum_{i=1}^{6} \psi_i r^e_{B,i,t} + v_t, \tag{8}$$

where $r^e_{B,i,t}$ denotes the excess return of base asset i, and $\mathbb{E}(v_t)=0$ and $\mathbb{E}(v_t \times r^e_{B,i,t})=0$, for $i=1,\ldots,6$. The portfolio-mimicking invention activity uses the

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estimated regression slope coefficients as portfolio weights. Its excess return, given by

$$r^e_{\tilde{N},t} = \sum_{i=1}^{6} \hat{\psi}_i r^e_{B,i,t}, \tag{9}$$

then serves as an alternative proxy for invention growth. The proxy retains the pricing information of the original risk factor but is less prone to measurement error, and it can be conveniently expressed in the form of an excess return. Moreover, using a mimicking portfolio provides a robustness check because, as Kan and Robotti (2009) point out, the statistical significance of the risk factors may be overstated if, as in the present case, nontraded factors are used.

We use the simple return of the value-weighted New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and NASDAQ traded stocks, denoted r_W, as a proxy for $\Delta W/W$. The test assets in our main analysis are the excess returns (over the 1-month T-bill rate) of the 25 size- and book-to-market-sorted Fama–French portfolios. We report the value-weighted portfolios results in the main text; results for equal-weighted portfolios appear in the Internet Appendix (see Appendix Section A). The data are retrieved from Kenneth French's financial data library, which is also the source for the Fama–French factors SMB and HML, as well as the six base assets.[5]

B. Descriptive Analysis

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, as we mentioned previously, our proxy for invention activity is prone to measurement errors, which become exacerbated at higher sampling frequencies. Second, a longer time series can capture more periods of creative destruction. For comparison and a robustness check, we also use quarterly postwar data from 1950:Q1–2008:Q4.

Panel A in Table 1 reports descriptive statistics on patenting growth, market return, and the 2 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% per year. The average excess returns of the size and value investment strategies are 3.6% (SMB) and 5.1% (HML), respectively. Considerable size and value effects in the long run also become apparent in Panel B of Table 1, which reports the means and standard deviations of the excess returns of the size- and book-to-market-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 portfolio, with an average annual excess return of 3.7%, is the notorious exception.

[5] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html, accessed Apr. 1, 2010 and Nov. 9, 2009 (base assets). Due to frequent changes in the underlying Center for Research in Security Prices (CRSP) data, newer downloads will yield somewhat different series. Annual data come directly from Kenneth French's data library, and we compute the quarterly excess returns from the monthly series.

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TABLE 1
Descriptive Statistics

Panel A of Table 1 reports the means, standard deviations, first-order autocorrelations ($\rho(1)$), and correlations of the market return proxy (r_W), SMB, HML, patenting growth (pg), and the excess return of the invention-mimicking portfolio (r_N^e). Panel B shows the summary statistics for the yearly excess returns of the 25 value-weighted portfolios sorted by size (vertical) and book-to-market ratio. These excess returns are computed by subtracting the risk-free rate proxy (1-month T-bill rate) from the respective portfolio return. The financial data come from Kenneth French's data library; the patent data are from the USPTO. In Panel C, we display the covariances of the test portfolios' excess returns with the two proxies for invention activity growth, patenting growth and the excess return of the mimicking portfolio, respectively. The sample period is 1927–2008, and the sampling frequency is annual.

Panel A. Risk Factor Proxies

	Mean ×100	Std. Dev. ×100	$\rho(1)$	Correlations r_W	HML	SMB	pg
r_W	11.4	20.7	0.04				
HML	5.1	14.0	−0.01	0.12			
SMB	3.6	14.4	0.28	0.40	0.08		
pg	2.4	13.7	0.00	−0.06	−0.21	−0.21	
r_N^e	−1.7	4.4	0.25	−0.20	−0.67	−0.66	0.32

Panel B. Excess Returns of Size- and Book-to-Market-Sorted Portfolios

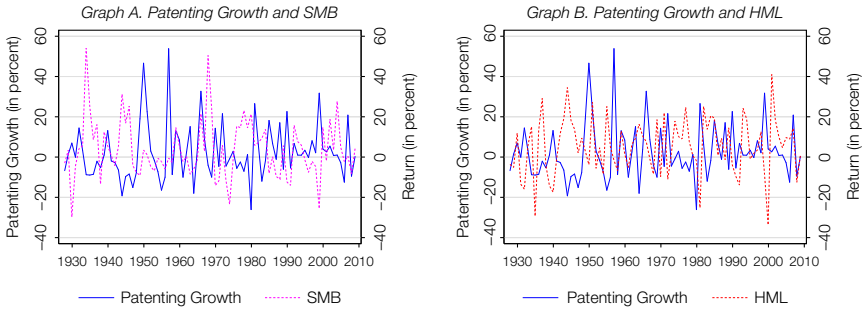
	Mean × 100					Std. Dev. × 100				
	Low	2	3	4	High	Low	2	3	4	High
Small	3.7	9.5	13.0	16.0	18.7	38.2	35.3	34.1	37.0	40.2
2	7.2	11.9	13.4	14.7	15.4	32.3	31.4	30.3	32.7	33.2
3	8.4	11.1	12.4	12.7	14.3	30.6	27.5	26.8	27.7	32.1
4	8.0	9.1	10.8	12.0	13.1	24.1	25.4	26.3	27.3	34.5
Big	7.2	7.1	8.3	8.5	10.0	21.5	19.5	22.1	25.2	31.8

Panel C. Covariances of Excess Returns with Proxies for Invention Activity (×100)

	Patenting Growth (pg)					Mimicking Portfolio Excess Return (r_N^e)				
	Low	2	3	4	High	Low	2	3	4	High
Small	−0.607	−0.756	−0.860	−1.051	−1.138	−0.458	−0.675	−0.830	−0.993	−1.072
2	−0.554	−0.639	−0.775	−0.781	−0.790	−0.471	−0.652	−0.748	−0.845	−0.820
3	−0.368	−0.638	−0.601	−0.753	−0.724	−0.329	−0.557	−0.608	−0.679	−0.796
4	−0.063	−0.450	−0.511	−0.689	−0.534	−0.113	−0.439	−0.535	−0.589	−0.653
Big	0.082	−0.244	−0.267	−0.389	−0.495	0.048	−0.174	−0.325	−0.398	−0.486

FIGURE 1
Patenting Growth and Fama–French Factors

Figure 1 shows patenting growth (in percent) and the Fama–French factors (SMB) and (HML) over the period 1927–2008.



Panel A in Table 1 shows that patenting growth exhibits little serial correlation and averages 2.4% annually, with a standard deviation comparable to that of SMB and HML. Furthermore, patenting growth negatively correlates 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 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.

Table 2 shows that the estimated invention-mimicking portfolio weights are jointly significant, although multicollinearity limits estimation precision, which is a common result in mimicking portfolio regressions (Lamont (2001), Vassalou (2003)). 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. Accordingly, the excess return of the mimicking portfolio is negatively correlated with HML and SMB, and its sample mean is negative (see Panel A in Table 1).

TABLE 2
Invention-Mimicking Portfolio

Table 2 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 an invention-mimicking portfolio. Base assets are the six portfolios sorted by size and book-to-market value (small-growth, small-neutral, small-value, big-growth, big-neutral, and big-value portfolios; Fama and French (1993)). The sample period is 1927–2008, and the frequency is annual. Coefficient estimates are reported in Panel A. The t-statistics (Panel B) are formulated for the null hypothesis that the true parameter is 0. The table also displays the coefficient of determination of the time-series regression (R^2_{ts}) and the p-value of a Wald test of the null hypothesis that $\gamma_1 = \gamma_2 = \cdots = \gamma_6 = 0$.

Panel A. Portfolio Weights

	Growth	Neutral	Value	Sum
Small	0.098	−0.244	−0.090	−0.236
Big	0.243	−0.099	0.092	0.236
Sum	0.341	−0.343	0.002	

Panel B. t

	Growth	Neutral	Value
Small	1.14	−1.31	−0.63
Big	2.01	−0.44	0.54
R^2_{ts}		10.3%	
p-value		1.5%	

Panel C in Table 1 reveals that all excess returns of the test assets except that of the large-growth portfolio covary negatively with patenting growth and the excess return of the invention-mimicking portfolio. The largest negative covariances appear in the upper right corners of the subpanels where small-value portfolios are located. Moreover, the correlations of the invention activity proxies and the value-weighted market portfolio are negative (see Panel A of Table 1). If the theoretical reasoning holds and the price of intertemporal risk γ_N is negative, then all test portfolios except the large-growth portfolio would be considered intertemporally risky assets (we investigate this issue further in Section V).[6] Although only the large-growth portfolio positively covaries with the risk factor proxies, it alone accounts on average for 35% of the total market value. On the other hand, firms in

[6]The related literature on asset prices and technological change offers alternative explanations for the contemporaneous relationship between asset returns and innovations. For example, Pástor and Veronesi (2009) argue that the uncertainty about the adoption of new technologies results in a systematic risk that pushes up discount rates and depresses prices in both old and new economies (after an initial run-up in new economy stocks). Gârleanu, Panageas, and Yu (2012) argue that on impact of a technological shock, growth options emerge in the prices of all securities. These growth options are riskier than assets in place and hence increase the volatility of equity prices and the risk premia in the initial phases of a technological cycle.

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the first size quintile make up only 2% of the entire market value (regarding the high concentration of market value among big firms, see also Fama and French (2008)).

IV. Econometric Methodology

We estimate the parameters of the CDRM in equation (5) by applying the 2-pass regression methodology, in which time-series regressions of the test assets' excess returns on the factor proxies $f_t = (r_W, pg)'$ and a constant yield estimates of $\beta_{W,i}$ and $\beta_{N,i}$. These estimated market and invention betas serve as explanatory variables in a 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. We also apply the GMM methodology proposed by Maio and Santa-Clara (2012) and estimate RRA and γ_N in the covariance representation in equation (4) of the CDRM. Moreover, we use the moment conditions in equation (6) to estimate the parameters b_W and b_N in the SDF representation of the CDRM by first-stage GMM. The resulting estimates are related as follows:

$$
\begin{aligned}
(10) \qquad \hat{\gamma} &= \begin{bmatrix} \widehat{\mathrm{RRA}} \\ \hat{\gamma}_N \end{bmatrix} = \begin{bmatrix} -\hat{b}_W \\ -\hat{b}_N \end{bmatrix} = -\hat{b} \\
&= \left[\mathrm{var}_T(f_t)\right]^{-1} \begin{bmatrix} \hat{\lambda}_W \\ \hat{\lambda}_N \end{bmatrix} = \left[\mathrm{var}_T(f_t)\right]^{-1} \hat{\lambda},
\end{aligned}
$$

where $\mathrm{var}_T(f_t)$ is the sample variance–covariance matrix of the risk factor proxies based on T time-series observations.[7]

Equation (10) holds for any linear factor model. The result is useful because a test of whether the creative-destruction risk factor is priced should focus on testing the statistical significance of $\hat{\lambda}_N$, whereas testing whether the risk factor proxy *patenting growth* is helpful in pricing the test assets should focus on assessing the significance of $\hat{b}_N$ or, equivalently, of $-\hat{\gamma}_N$ (Cochrane (1996)). Equation (10) shows that any of the three estimation approaches can be used to obtain the parameter estimates of interest. We chose to base the inference on the two-pass regression methodology, not only because it is more widely used, but also because it can be extended to account for the initial estimation of the mimicking portfolio weights and for a convenient specification test. These extensions, which we explain subsequently, represent the methodological contribution of our study.

We treat the 2-pass regression analysis as an instance of GMM, which offers several advantages. First, we can base the statistical inference on parameter estimates and pricing errors on less restrictive assumptions than Shanken's (1992) more widely used correction formulas.[8] Second, we can assess the statistical

[7] Although they are asymptotically equivalent, the estimates of the variance–covariance matrixes of the (implied) parameter estimates obtained by the three estimation methods will differ in finite samples. However, the differences are small, and they do not affect our conclusions. Because the results appear somewhat scattered in the literature, we provide details on the relationship of the three estimation approaches reflected in equation (10) as well as implications for statistical inference in Appendix Section D.

[8] There is no need to assume independence of factors and time-series regression residuals, and we can account for serial correlation among the regression residuals (Cochrane (2005), ch. 12.2).

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significance of the estimated risk compensations associated with creative destruction ($\hat{\beta}_{N,i} \times \hat{\lambda}_N$) as well as the implied $\widehat{\text{RRA}}$ and $\hat{\gamma}_N$ by using the joint variance–covariance matrix of the time series and the cross-sectional parameter estimates and by applying the delta method. Appendix Section B.1 explains the details. Third, we can draw on GMM theory to ensure proper inference when an invention-mimicking portfolio serves as a risk factor proxy.

To obtain such a mimicking portfolio version of the CDRM (MP-CDRM), we replace the risk factor proxy *patenting growth* with the excess return of the invention-mimicking portfolio, such that $\tilde{f}_t = (r_{W,t}, r^e_{\tilde{N},t})'$. We estimate the parameters of the resulting beta representation,

$$\mathbb{E}[r^e_{i,t}] \quad = \quad \beta_{W,i}\lambda_W + \beta_{\tilde{N},i}\lambda_{\tilde{N}} \quad = \quad \tilde{\beta}_i'\tilde{\lambda}, \tag{11}$$

where $\tilde{\beta}_i = \mathbb{E}[\tilde{f}^*_t \tilde{f}^{*'}_t]^{-1}\mathbb{E}[\tilde{f}^*_t r^e_{i,t}]$ and $\tilde{f}^*_t = \tilde{f}_t - \mathbb{E}(\tilde{f}_t)$, by a 2-pass regression analysis. The relationship of the parameters in the covariance representation of the MP-CDRM,

$$\begin{aligned} \mathbb{E}[r^e_{i,t}] &= \gamma_W \times \text{cov}\left[r^e_{i,t}, r_{W,t}\right] + \gamma_{\tilde{N}} \times \text{cov}\left[r^e_{i,t}, r^e_{\tilde{N},t}\right] \\ &= \tilde{\gamma}'\mathbb{E}\left[\tilde{f}^*_t r^e_{i,t}\right], \end{aligned} \tag{12}$$

and its SDF representation, $\mathbb{E}[(1 + \tilde{b}'\tilde{f}^*_t) r^e_{i,t}] = 0$, where $\tilde{b} = (b_W, b_{\tilde{N}})'$, is analogical to equation (7). Moreover, there is a counterpart to equation (10), which connects the cross-sectional regression slope estimates $\hat{\lambda}_W$ and $\hat{\lambda}_{\tilde{N}}$, the estimates of γ_W and $\gamma_{\tilde{N}}$ obtained using Maio and Santa-Clara's (2012) GMM approach, and the first-stage GMM estimates $\hat{b}_W$ and $\hat{b}_{\tilde{N}}$ using the moment conditions implied by the SDF representation of the MP-CDRM.

Proper statistical inference in this setup must account for the fact that the mimicking portfolio weights are estimated. We therefore collect all moment restrictions implied by the MP-CDRM, namely, the orthogonality conditions from equation (8), those from the time-series regressions of test asset excess returns on $r_{W,t}$ and $r^e_{\tilde{N},t}$, and those that follow from equation (11), namely, $\mathbb{E}[r^e_{i,t}] - \tilde{\beta}_i'\tilde{\lambda} = 0$, for $i = 1, \ldots, K$, where K denotes the number of test assets. GMM theory then provides the variance–covariance matrix of all parameter estimates and the variance–covariance matrix of the average pricing errors. See Appendix Section B.2 for details.

Applying GMM theory also facilitates a model specification test that is inspired by Lewellen et al. (2010). Because $r^e_{\tilde{N},t}$ is an excess return, it follows that $\lambda_{\tilde{N}} = \mathbb{E}[r^e_{\tilde{N},t}]$. This identity can be exploited for a model specification test that focuses on the statistical significance of the difference between $\hat{\lambda}_{\tilde{N},cs}$, the cross-sectional slope estimate of $\lambda_{\tilde{N}}$, and the time-series estimate $\hat{\lambda}_{\tilde{N},ts} = \frac{1}{T}\sum_{t=1}^{T} r^e_{\tilde{N},t}$. Large positive or negative deviations of $\Delta\hat{\lambda} = \hat{\lambda}_{\tilde{N},cs} - \hat{\lambda}_{\tilde{N},ts}$ from 0 then indicate model misspecification. To conduct statistical inference about $\Delta\hat{\lambda}$, we augment the set of moment conditions by $\lambda_{\tilde{N}} - \mathbb{E}[r^e_{\tilde{N},t}] = 0$ and construct a Wald-type test statistic that is based on the difference of the two estimates:

$$W_{\Delta\lambda} \quad = \quad \frac{\Delta\hat{\lambda}^2}{\widehat{\text{var}}(\hat{\lambda}_{\tilde{N},cs}) - 2\widehat{\text{cov}}(\hat{\lambda}_{\tilde{N},cs}, \hat{\lambda}_{\tilde{N},ts}) + \widehat{\text{var}}(\hat{\lambda}_{\tilde{N},ts})}. \tag{13}$$

Under the null hypothesis that the model is correctly specified, the distribution of $W_{\Delta\lambda}$ is approximately $\chi^2(1)$. When constructing $W_{\Delta\lambda}$, we rely on the variance–covariance matrix of all parameter estimates, which is obtained from GMM theory. We thereby account for three peculiarities: the mimicking portfolio weights are estimated, the beta estimates come from a time-series regression, and $\hat{\lambda}_{\tilde{N},cs}$ and $\hat{\lambda}_{\tilde{N},ts}$ are correlated.

For further assessments of goodness of fit and model specification, we focus on the average pricing errors $\hat{\alpha}_i = \frac{1}{T}\sum r^e_{i,t} - \hat{\beta}_{W,i}\hat{\lambda}_W - \hat{\beta}_{N,i}\hat{\lambda}_N$ and $\hat{\alpha}_i = \frac{1}{T}\sum r^e_{i,t} - \hat{\beta}_{W,i}\hat{\lambda}_W - \hat{\beta}_{\tilde{N},i}\hat{\lambda}_{\tilde{N}}$, respectively. Collecting the average pricing errors for the K test assets in the vector $\hat{\alpha} = (\hat{\alpha}_1, \ldots, \hat{\alpha}_K)'$, we compute the mean absolute pricing error (MAE),

$$\text{MAE} = \frac{1}{K}\sum_{k=1}^{K} |\hat{\alpha}_k| \times 100, \tag{14}$$

and the cross-sectional coefficient of determination,

$$R^2_{cs} = \left[1 - \frac{\text{var}_K(\hat{\alpha}_i)}{\text{var}_K(\overline{r}^e_i)}\right] \times 100, \tag{15}$$

where $\overline{r}^e_i = \frac{1}{T}\sum_{i=1}^{T} r^e_{i,t}$, and $\text{var}_K(\cdot)$ denotes a cross-sectional sample variance.[9]

The average pricing errors also serve to construct the test statistic

$$J = \hat{\alpha}'\widehat{\text{var}}(\hat{\alpha})^{+}\hat{\alpha}, \tag{16}$$

where $\widehat{\text{var}}(\hat{\alpha})^{+}$ is the Moore–Penrose inverse of the estimated variance–covariance matrix of $\hat{\alpha}$. GMM theory yields the expression for $\widehat{\text{var}}(\hat{\alpha})$ and the result that $J \overset{a}{\sim} \chi^2(K-2)$ under the null hypothesis that CDRM or MP-CDRM, respectively, holds unconditionally (see Appendix Section B for details).

We complement the GMM inference with bootstrapped p-values for the MAE, the R^2_{cs}, and the t-statistics associated with the price of risk estimates, as suggested by Maio and Santa-Clara (2012). Appendix Section C explains the details.

V. Main Empirical Results

Table 3 reports the beta estimates and the associated t-statistics of the CDRM (Panel A) and the MP-CDRM (Panel B). The time-series coefficients of determination are given in Panel C. Invention betas vary across test assets, with a discernible pattern that corresponds to that of the covariances in Panel C of Table 1. Large negative $\hat{\beta}_N$ and $\hat{\beta}_{\tilde{N}}$ appear in the upper right corners of the panels where small and high book-to-market portfolios are located. The small-value portfolio has the strongest negative exposure to invention activity, whereas the invention beta for the large-growth portfolio is positive.

Panel A of Table 4 reveals that the estimates of λ_N and $\lambda_{\tilde{N}}$ have the hypothesized negative sign, and the same holds true for the estimates of γ_N and $\gamma_{\tilde{N}}$. Both

[9] Although the maximum value of the R^2_{cs} is 100, its lower limit is not 0. One should therefore refrain from interpreting it as a percentage (of explained variance over total variance).

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TABLE 3

Time-Series Regression Results for CDRM and MP-CDRM (Annual Data)

Panel A of Table 3 reports the beta estimates from time-series regressions of excess returns on the CDRM risk factor proxies, the return of the wealth portfolio proxy (r_W), and patenting growth (pg). The test assets are the 25 value-weighted portfolios sorted by size (vertical) and book-to-market value (horizontal). Panel B reports the beta estimates from time-series regressions of the test assets' excess returns on r_W and the invention-mimicking portfolio's excess return, $r^e_{\tilde{N}}$. Panel C displays the coefficient of determination of each time-series regression (R^2_{ts}). The sample period is 1927–2008, and the frequency is annual.

	Low	2	3	4	High	Low	2	3	4	High
Panel A. CDRM										
	$\hat{\beta}_W$					t				
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				
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
Panel B. MP-CDRM										
	$\hat{\beta}_W$					t				
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
	$\hat{\beta}_{\tilde{N}}$					t				
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
Panel C. Time-Series Coefficient of Determination										
	R^2_{ts} (%)									
	CDRM					MP-CDRM				
Small	61.1	69.2	71.4	67.0	67.1	62.0	75.5	85.1	85.6	85.2
2	72.7	76.3	74.5	72.6	71.6	74.8	84.5	88.5	89.3	86.2
3	76.3	80.9	79.1	78.0	67.7	76.7	87.7	89.7	91.0	83.1
4	83.7	79.2	81.8	75.8	69.3	84.2	83.4	89.2	84.5	76.1
Big	87.2	91.6	82.2	78.5	71.3	92.7	91.5	84.4	81.5	74.1

bootstrap and GMM inference indicate that these estimates are statistically significant. The bootstrapped p-values are 1.9% ($\hat{\lambda}_N$), 0.1% ($\hat{\lambda}_{\tilde{N}}$), 2.3% ($\hat{\gamma}_N$), and 0.3% ($\hat{\gamma}_{\tilde{N}}$).[10] The significant estimates $\hat{\lambda}_{\tilde{N}}$ and $\hat{\lambda}_N$ suggest that invention growth is a priced risk factor, and the significant estimates $\hat{\gamma}_N$ and $\hat{\gamma}_{\tilde{N}}$ indicate that the creative-destruction risk factor proxies are helpful in pricing the test assets.

Panels A and B of Table 5 show that the estimated risk compensations associated with creative-destruction risk are economically substantial. Large positive and statistically significant $\hat{\beta}_N \times \hat{\lambda}_N$ and $\hat{\beta}_{\tilde{N}} \times \hat{\lambda}_{\tilde{N}}$ appear where small and high book-to-market portfolios are located, whereas the estimated risk compensation

[10]Unless noted otherwise, all reported p-values are for t-statistics with the null hypothesis that the true parameter is 0.

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TABLE 4

Cross-Sectional Regression and Test Results

Table 4 reports the cross-sectional estimation results for the CDRM, MP-CDRM, and benchmark models. We report the lambda estimates and the estimates of the RRA coefficient (CDRM and Fama–French model) and γ_N and $\gamma_{\tilde{N}}$ (CDRM and MP-CDRM). Panels A and B report the results based on annual data from 1927–2008. For the Panel A results, we use the excess returns of the value-weighted size- and book-to-market-sorted portfolios as test assets. For the Panel B results, we complement these test assets by the excess returns of 17 industry portfolios. Panel C reports the results for the quarterly postwar sample 1950:Q1–2008:Q4, with the value-weighted size- and book-to-market-sorted portfolios as the test assets. We also report the cross-sectional coefficient of determination (R^2_{cs}), the MAE, the *p*-values associated with the *J*-statistic, and the Wald statistic in equation (13). The *J*- and *t*-statistics are based on GMM inference as outlined in Appendix Section B. *t*-statistics for the null hypothesis that the true parameter is 0 are reported in parentheses. The bootstrapped *p*-values for the *t*-statistics, R^2_{cs}, and MAE are reported in square brackets. The null hypothesis for the latter two is that the model has no explanatory power (see Appendix Section C).

	$\hat{\lambda}_W$	$\hat{\lambda}_{HML}$	$\hat{\lambda}_{SMB}$	$\hat{\lambda}_N$ or $\hat{\lambda}_{\tilde{N}}$	$\widehat{RRA}$	$\hat{\gamma}_N$ or $\hat{\gamma}_{\tilde{N}}$	J [%]	R^2_{cs}	$W_{\Delta\lambda}$ [%]	MAE
Panel A. Size- and Book-to-Market-Sorted Portfolios (Annual Data)										
CDRM	0.066 (2.84) [0.5%]			−0.148 (−2.36) [1.9%]	1.220 (2.09) [4.0%]	−7.806 (−2.31) [2.3%]	1.4	49.6 [8.7%]		1.62 [3.0%]
MP-CDRM	0.061 (2.60) [0.8%]			−0.021 (−2.80) [0.1%]		−10.092 (−2.47) [0.3%]	1.5	63.3 [3.5%]	56.1	1.38 [0.8%]
Fama–French	0.068 (2.89) [0.5%]	0.060 (3.73) [<0.1%]	0.035 (2.04) [4.8%]		1.123 (1.82) [8.1%]		1.6	70.6 [4.8%]		1.39 [2.1%]
CAPM	0.090 (3.91) [<0.1%]						0.2	23.8 [9.3%]		2.22 [5.9%]
Panel B. Including Industry Portfolios (Annual Data)										
CDRM	0.069 (2.96) [0.4%]			−0.132 (−2.80) [0.7%]	1.325 (2.35) [2.1%]	−6.929 (−2.74) [0.8%]	0.3	46.2 [1.0%]		1.53 [0.1%]
MP-CDRM	0.067 (2.86) [0.4%]			−0.018 (−2.49) [0.2%]		−8.330 (−2.11) [0.9%]	2.6	43.9 [1.3%]	81.0	1.62 [0.3%]
Fama–French	0.076 (3.20) [0.2%]	0.050 (3.06) [0.2%]	0.033 (2.04) [6.0%]		1.396 (2.21) [3.8%]		0.9	45.2 [3.1%]		1.59 [0.6%]
CAPM	0.094 (4.07) [<0.1%]						1.1	14.8 [3.0%]		1.92 [0.5%]
Panel C. Size- and Book-to-Market-Sorted Portfolios (Quarterly Postwar Data)										
CDRM	0.015 (2.71) [0.3%]			−0.154 (−1.92) [5.1%]	1.838 (2.10) [3.4%]	−9.655 (−1.91) [5.5%]	7.6	−22.3 [29.1%]		0.57 [20.5%]
MP-CDRM	0.013 (2.34) [1.2%]			−0.005 (−1.91) [0.6%]		−13.304 (−1.69) [1.8%]	0.8	2.6 [17.4%]	82.1	0.50 [11.4%]
Fama–French	0.017 (3.06) [<0.1%]	0.014 (3.77) [<0.1%]	0.005 (1.42) [18.2%]		3.751 (4.02) [<0.1%]		0.1	69.0 [0.9%]		0.26 [0.1%]
CAPM	0.020 (3.63) [<0.1%]						<0.1	−61.7 [30.2%]		0.66 [14.3%]

associated with creative-destruction risk is negative for the large-growth portfolio.[11]

On the basis of the CDRM results, we estimate an additional expected excess return compensation of 6.8 percentage points per annum for the small-

[11] Using $\widehat{\text{cov}}(pg, r^e) \times \hat{\gamma}_N$ to measure the compensation for creative-destruction risk yields the same conclusions, but we prefer $\hat{\beta}_N \times \hat{\lambda}_N$ because it facilitates GMM inference.

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TABLE 5

Estimated Risk Compensations Associated with Creative Destruction

Table 5 reports estimated expected excess return compensations that are implied by the CDRM and MP-CDRM, respectively. Panel A shows the CDRM results, and Panel B shows the MP-CDRM results, both for annual data, 1927–2008. Panel C shows the CDRM results, and Panel D shows the MP-CDRM results, both for quarterly data, 1950:Q1–2008:Q4. Test assets are the 25 portfolios sorted by size (vertical) and book-to-market value (horizontal). The delta method is used to compute the t-statistic for a test that the respective risk compensation is 0. See Appendix Section B for details.

	Low	2	3	4	High	Low	2	3	4	High
	$\hat{\beta}_N \times \hat{\lambda}_N \times 100$					t				
Panel A. CDRM (Annual Data)										
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
	$\hat{\beta}_{\tilde{N}} \times \hat{\lambda}_{\tilde{N}} \times 100$					t				
Panel B. MP-CDRM (Annual Data)										
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
	$\hat{\beta}_N \times \hat{\lambda}_N \times 4 \times 100$					t				
Panel C. CDRM (Quarterly Postwar Data)										
Small	4.4	3.8	4.4	4.8	5.1	1.35	1.76	2.34	2.62	2.68
2	2.3	2.7	1.7	3.8	4.2	1.19	1.75	1.20	2.61	2.35
3	0.5	3.3	2.7	2.3	3.8	0.29	2.47	2.01	1.73	1.91
4	0.2	2.7	2.5	2.8	2.0	0.14	2.06	2.07	1.94	1.40
Big	−1.6	−0.9	0.8	1.3	1.2	−1.86	−0.87	0.73	0.95	0.53
	$\hat{\beta}_{\tilde{N}} \times \hat{\lambda}_{\tilde{N}} \times 4 \times 100$					t				
Panel D. MP-CDRM (Quarterly Postwar Data)										
Small	4.9	5.8	5.9	6.2	7.7	1.26	1.86	2.30	2.48	2.59
2	3.0	4.4	4.4	5.3	6.6	0.99	1.97	2.37	2.69	2.54
3	1.2	2.9	3.7	4.4	6.0	0.53	2.04	2.53	2.36	2.36
4	−0.1	2.0	2.7	3.4	4.9	−0.07	1.86	2.04	2.11	1.86
Big	−2.3	−0.5	0.2	1.8	2.6	−1.96	−0.55	0.17	0.92	0.89

value portfolio (p-value = 0.5%). For the large-growth portfolio, we estimate an expected return discount of −2.0 percentage points (p-value = 7.1%).[12] The MP-CDRM accentuates these results, with an estimated expected return compensation of 9.0 percentage points per annum for the small-value portfolio (p-value = 0.5%) and an estimated expected return discount of −2.7% for the large-growth portfolio (p-value = 0.4%).

The differences in the expected excess return compensations for portfolios with the highest positive and negative exposure to creative-destruction risk are statistically significant; the corresponding p-value is 0.3% for the CDRM. These results are in accord with the reasoning that small-value stocks are 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 earn-

[12]These results are even more pronounced for equal-weighted test portfolios. For the small-value portfolio, we estimate a risk compensation of 11.3 percentage points (p-value = 0.1%), whereas we estimate an expected return discount of −2.3 percentage points (p-value = 1.8%) for the large-growth portfolio. Detailed results for equal-weighted portfolios can be found in the Internet Appendix (see Appendix Section A).

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ings growth and high profitability ratios, are more likely to withstand periods of creative destruction. An investment in large-growth stocks provides protection against creative-destruction risk, leading to the expected return discount.[13]

Panel A of Table 4 reports the results of model specification tests and empirical goodness-of-fit analyses, including a comparison with the static CAPM and the Fama–French (1995) model. The CAPM 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_W^e) as risk factors offers an obvious benchmark. Such a comparison is not a race for the best goodness of fit, though. As Cochrane (2008) recognizes, portfolio-based models, such as the Fama–French model, have a head start when estimated using portfolios sorted by size and book-to-market value, which exhibit a correlation structure that is well captured by three principal components (Lewellen et al. (2010)). Static CAPM and the Fama–French model instead serve as reference points for assessing the ability of the CDRM to account empirically for size and value premia. Again, we adopt the GMM view on 2-pass regression analysis when estimating and testing the CAPM and the Fama–French model.

The J-test rejects all models at the 5% level, yet neither the CDRM and MP-CDRM nor the Fama–French model is rejected at 1%. Moreover, the MP-CDRM is not rejected at conventional significance levels by the specification test that focuses on the difference between the time-series and cross-sectional estimates of $\lambda_{\tilde{N}}$. The p-value associated with the Wald statistic $W_{\Delta\lambda}$ in equation (13) is 56.1%.[14]

The cross-sectional goodness-of-fit results for the CAPM and the Fama–French model are unsurprising. The CAPM's explanatory power is smallest with an R^2_{cs} of 23.8, whereas the Fama–French model's R^2_{cs} is 70.6. The CDRM achieves a considerably higher goodness of fit than the CAPM; the R^2_{cs} is 49.6. The bootstrap p-values for R^2_{cs} show that at the 10% significance level, the hypothesis of no explanatory power can be rejected for all models; for the MP-CDRM, the hypothesis is also rejected at 5%. The bootstrap p-values for the MAE show that for both CDRM variants, the null hypothesis of no explanatory power can be rejected at the 5% level.

Figure 2 illustrates the models' goodness of fit by depicting the average excess returns of the test assets against the model-implied excess returns. Graph A reveals the notorious deficiency of the static CAPM to account for cross-sectional average return differences across size- and book-to-market-sorted

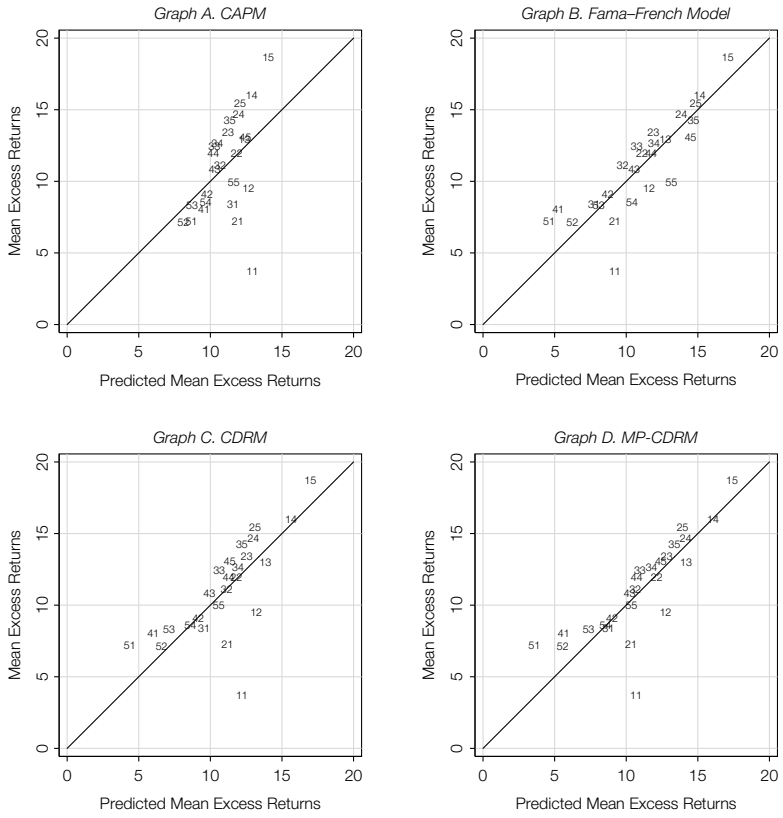
[13]The invention beta of small-growth firms is negative, indicating that investing in these stocks would be a poor hedge against creative-destruction risk. The case study by Goldfarb, Kirsch, and Miller (2007) is in line with that conclusion. They document a low survival rate of small but relatively highly valued technology firms during the dot-com era.

[14]Lewellen et al. (2010) argue that a model that aims to explain size and value premia also requires an assessment of whether it can price HML and SMB. However, a 2-pass regression analysis of the CDRM that uses the Fama–French factors as test assets does not imply restrictions that are testable with a J-test because the number of test assets equals the number of risk factors. We therefore focus on the difference of time-series and cross-sectional estimates of $\lambda_{\tilde{N}}$ and compute the Wald statistic $W_{\Delta\lambda}$ in equation (13). Using Fama–French factors instead of size- and book-to-market-sorted portfolios as test assets, we obtain a similar but less precise cross-sectional estimate of $\hat{\lambda}_{\tilde{N},cs}$ equal to -0.024 (p-value $= 11.4\%$). The difference from the (unchanged) time-series estimate is, with a p-value of 69.2% associated with $W_{\Delta\lambda}$, not significantly different from 0; thus, the MP-CDRM cannot be rejected at conventional levels of significance.

FIGURE 2

Predicted versus Actual Mean Excess Returns for the CAPM, Fama–French Model, CDRM, and MP-CDRM

Figure 2 compares the predicted and realized average excess returns (percentage) given by the CAPM (Graph A), the Fama–French model (Graph B), the CDRM (Graph C), and the MP-CDRM (Graph D). The sample period is 1927–2008; the sampling frequency is annual. The test assets are the 25 value-weighted portfolios sorted by size and book-to-market value, where the first number denotes the size quintile (1 = smallest; 5 = largest), and the second number refers to the book-to-market quintile (1 = lowest; 5 = highest).



portfolios. Graph B shows that the Fama–French model is predictably more successful, but the CDRM (Graph C) also improves the empirical fit considerably. Both CDRM variants do a particularly good job in pricing the small-value portfolios. The premium for creative-destruction risk thus corrects to some extent for the mispricing of the CAPM.[15]

[15]Neither the Fama–French model nor the CDRM can account for the small average excess return of the small-growth portfolio, which poses a long-standing challenge for empirical asset pricing (Campbell and Vuolteenaho (2004), Yogo (2006)). D'Avolio (2002), Mitchell, Pulvino, and Stafford (2002), and Lamont and Thaler (2003) document limits to arbitrage due to short-sale constraints, which may explain why it is difficult to price the small-growth portfolio.

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VI. Industry Portfolios, Postwar Data, and Further Analysis

A. Industry Portfolios

To verify the robustness of our results, we follow the prescription of Lewellen et al. (2010) and augment the 25 size- and book-to-market-sorted test portfolios by industry portfolios, thereby taking into account the aforementioned problem of commonalities in the Fama–French portfolios. For our study context, considering industry portfolios is interesting in itself because some industries may be more exposed to the risk of creative destruction than others. We focus on the excess returns of the 17 industry portfolios that are available on Kenneth French's home page.[16]

Panel B of Table 4 shows that the CDRM estimation results are robust when we include industry portfolios among the test assets. The estimates $\hat{\lambda}_N$ and $\hat{\gamma}_N$ again show the negative sign that is consistent with theoretical reasoning. The estimation precision even improves, relying on both GMM and bootstrap inferences. The size of these point estimates is comparable to that of the analysis that uses size- and book-to-market-sorted portfolios only. The cross-sectional coefficient of determination delivered by the CDRM barely changes when we include industry portfolios, and the MAE even improves. By contrast, the R^2_{cs} of the Fama–French model decreases substantially with the inclusion of industry portfolios. The CDRM delivers a higher R^2_{cs} and a smaller MAE than the Fama–French model. The null hypothesis of no explanatory power is clearly rejected, as indicated by the p-values associated with MAE and the R^2_{cs}. Cross-sectional and time-series estimates of $\lambda_{\tilde{N}}$ are very similar (-0.018 vs. -0.017); accordingly, the p-value of the Wald statistic that tests the significance of their difference is 81.0%.

Figure 3 visualizes the comparable explanatory power of the Fama–French model and CDRM in the cross section, with some advantages for the CDRM, in particular regarding the industry portfolios. We take it as an encouraging result that a model with one additional economically motivated risk factor delivers an empirical performance that matches that of the 3-factor benchmark model.

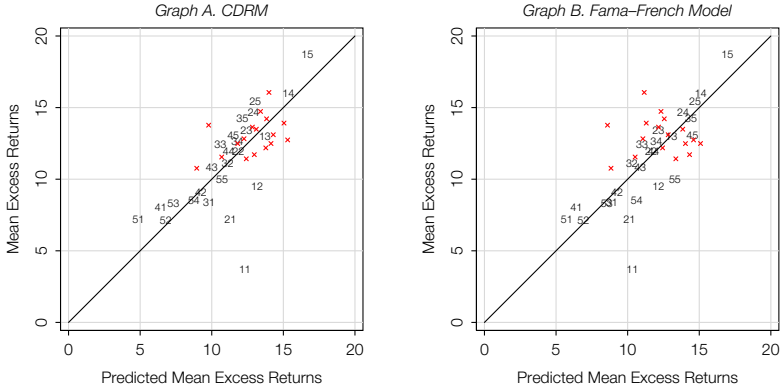
We also note a caveat in relation to industry portfolios, though. Their invention betas likely change depending on the time period and the extent to which certain industries suffer exposure to creative-destruction risk. To study the time-varying exposure, we perform rolling time-series regressions for different industry portfolios using a 40-year window. Indeed, we find that the estimates of the invention betas change over time, consistent with Fama and French's (1997) work on industry costs of capital, in which they show that exposures of industries to the market, SMB, and HML vary over time. Moreover, the results for specific industries are consistent with our conclusions. For example, the patenting growth betas for high-tech and telecommunications industries are close to 0 prior to the mid-1990s but then become positive, leveling at a point estimate of around 1 during the first decade of the new millennium. As discussed previously,

[16] We use the equal-weighted portfolios because we do not want to confound size with industry effects. Moreover, the average returns of value-weighted industry portfolios exhibit little cross-sectional variation, so there is not much to explain except the equity premium.

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FIGURE 3
Predicted versus Actual Mean Excess Returns Including Industry Portfolios

Figure 3 compares predicted with realized average excess returns (percentage) given by the CDRM (Graph A) and the Fama–French model (Graph B). The sample period is 1927–2008; the sampling frequency is annual. The test assets are the 25 value-weighted portfolios sorted by size and book-to-market value and 17 industry portfolios (indicated by red crosses). The first number denotes the size quintile (1 = smallest; 5 = largest), and the second number refers to the book-to-market quintile (1 = lowest; 5 = highest).



a positive patenting growth beta means that such an asset represents a hedge against creative-destruction risk.

B. Postwar Sample

In the previous section, we adopted a long-run, low-frequency perspective to capture more periods of creative destruction and avoid measurement errors in the patenting data. However, many empirical tests of asset pricing models instead use postwar data sampled at a quarterly frequency. To achieve comparable results and provide an additional robustness check, we perform the empirical analysis using quarterly data from 1950:Q1–2008:Q4.

The quarterly/postwar results reported in Panels C and D of Table 4 corroborate the conclusions of the annual/long-run analysis. The estimates of λ_N and $\lambda_{\tilde{N}}$ have the hypothesized negative sign, and the same holds true for the estimates of γ_N and $\gamma_{\tilde{N}}$. The associated t-statistics and bootstrap p-values suggest that invention growth is a priced risk factor, and the significant estimates $\hat{\gamma}_N$ and $\hat{\gamma}_{\tilde{N}}$ indicate that the creative-destruction risk factor proxies are helpful in pricing the test assets. The explanatory power improves relative to the CAPM, even if not as much as to rival the Fama–French model, and to a lesser extend compared with the annual/long-run analysis. The MP-CDRM is constructed to alleviate measurement errors in the patenting data, which are aggravated at quarterly sampling frequencies. Indeed, the MP-CDRM's cross-sectional fit measures of MAE and R^2_{cs} improve on those of the CDRM, and the model is not rejected by the J-test at the 1% significance level. Moreover, the p-value associated with the Wald statistic $W_{\Delta\lambda}$ in equation (13) is 58.5%, such that the MP-CDRM cannot be rejected at conventional levels of significance.

Panels C and D of Table 5 shows that the cross-sectional pattern, size, and statistical significance of the estimated compensations for creative-destruction

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risk are again in line with theoretical reasoning. Large estimated compensations for creative-destruction risk cluster where small and high book-to-market portfolios are located, and again the biggest expected return discount refers to the large-growth portfolio.

C. Additional Analyses

The Internet Appendix contains the detailed results of further analyses (see Appendix Section A). In particular, we report the estimation results using single-sorted size and book-to-market decile portfolios. Using these test assets, the performance of the CDRM is comparable to that of the Fama–French model. We also consider a high-invention minus low-invention beta portfolio as an alternative creative-destruction risk factor proxy, which yields similar results as when using pg or the mimicking portfolio. Moreover, we study an ad hoc 4-factor model with the market return, pg, and orthogonalized Fama–French factors. We find that when using size- and book-to-market-sorted portfolios as test assets, the pricing information contained in pg is captured by the Fama–French factors. However, the result changes when we augment the set of test assets by industry portfolios. In this case, pg dominates the orthogonalized Fama–French factors in terms of relevance for pricing.

VII. Discussion: Logical Consistency of the CDRM and Alternative Explanations

Maio and Santa-Clara (2012) delineate requirements that an empirical multifactor asset pricing model must meet to be consistent with the ICAPM: It should deliver reasonable estimates of the price of intertemporal risk and the model-implied RRA coefficient, and the ICAPM state variable should predict future changes in wealth.

Because we motivate the CDRM by basing it on the ICAPM framework, examining whether these conditions are empirically supported in the present case is a useful plausibility check. We initiated this task in the previous section. Recall that our theoretical reasoning implies that $\lambda_N < 0$ and $\gamma_N < 0$. The negative signs of the estimates $\hat{\lambda}_N$ and $\hat{\gamma}_N$ reported in Panels A and B of Table 4 are therefore consistent with the theoretical motivation of the CDRM. Using equation (10), we also obtain an estimate of the RRA coefficient, which should lie in the range between 1 and 5, describing reasonably risk-averse investors. Panel A in Table 4 shows that the CDRM estimate ($\widehat{\text{RRA}} = 1.22$) is similar to that implied by the Fama–French model ($\widehat{\text{RRA}} = 1.12$). Panel B shows that same conclusion holds true when industry portfolios are included in the set of test assets (CDRM: $\widehat{\text{RRA}} = 1.33$; Fama–French model: $\widehat{\text{RRA}} = 1.40$). These point estimates thus represent plausible coefficients of RRA.[17] Although we do find some evidence that invention activity predicts market returns, the negative impact of invention shocks on the value of future human capital of extant agents (the displacement effect) cannot be measured by checking the predictability of the returns of a portfolio that consists only

[17]However, it should be noted that in both cases, the 95% confidence intervals overlap the log-utility case (RRA = 1), for which the ICAPM reduces to the static CAPM.

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of financial assets. However, the cohort effects in consumption found by Gârleanu, Kogan, and Panageas (2012) provide empirical evidence for the displacement effect and thus, indirectly, support the logical consistency of the CDRM. Overall, the CDRM performs comparably well in empirical verifications of its consistency with the ICAPM. Among the multifactor models compared by Maio and Santa-Clara (2012), only the Fama–French model and the Carhart (1997) model are able to meet all requirements for ICAPM consistency, but these specifications, unlike the CDRM, lack economic content.

The ICAPM provides a justification for why invention activity should enter as a priced factor, but we also could draw on Fama and French (1996) and Cochrane (2005) to motivate an asset pricing model that accounts for creative-destruction risk and thereby explain our empirical results. In his reflections on multifactor models, Cochrane (2005) points out that most investors have jobs, such that assuming pure (retired) investors, who are concerned only about financial wealth invested in traded stocks and bonds, and for whom the market return is thus the sole risk factor, is questionable. Instead, most investors face layoff risk and prefer stocks that are resilient to economy-wide negative shocks. Such shocks include not only recessions but also bursts of invention activity that imperil the value of human capital of job-holding investors and extant businesses. By demanding stocks that are resilient to negative shocks (i.e., arguably, large-growth stocks), investors drive up their prices and push down their expected returns. In contrast, firms that are more vulnerable to the negative macro-shocks (i.e., value firms) get avoided, with their prices pushed down and their expected returns driven up. Expected returns therefore should depend on additional betas that reflect the risks that employed investors consider. In the context of our study, an invention activity beta, as in equation (5), represents such a consideration.

In a similar vein, Fama and French (1996) explain why relative distress emerges as a state variable that is of special hedging concern to investors. Their reasoning resembles the ICAPM motivation of the CDRM, but it dispenses with the intergenerational aspects emphasized by Gârleanu, Kogan, and Panageas (2012). The explanation also involves imperiled human capital, and the displacement effect provides the link to invention activity and creative destruction. In particular, Fama and French (1996) argue that a negative macro-shock to a large-growth firm's prospects may not severely affect the value of the human capital of a worker who has specialized human capital tied to the firm. In contrast, a negative macro-shock to a distressed/value firm, which in the present context would be associated with a burst in invention activity, likely implies a negative impact on the value of specialized human capital connected to the firm. Future employment in the firm is more likely to contract. As a result, workers with specialized human capital linked to distressed firms avoid holding their firms' stocks. When variation in distress correlates across firms, workers have an incentive to avoid the stocks of all distressed firms. The result can be a state-variable risk premium in the expected returns of distressed stocks. Our derivation of the CDRM is based on a similar logic that recognizes the exposure to invention activity, or creative-destruction risk, as the source of firm distress.

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VIII. Conclusion

Consider the range of technological changes in the past century. Creative-destruction processes have been pivotal for economic growth but have also presented substantial risks for investments in extant firms. Imagine a John Doe (J. D.), born in 1940, who began to work at the age of 20 and started investing in the midst of the technological revolution of the 1950s and 1960s. Assuming a retiring age of 65 years, J. D. started to consume savings in 2005, after the peak of an information technology wave. At this point, he still had a remaining life expectancy of 19 years.[18] 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 has posed a considerable risk for J. D.'s past investments, and it will continue to be one in his retirement years.

As our study shows, some cross-sectional return differences across size- and book-to-market-sorted portfolios can be explained as premia for bearing or hedging against creative-destruction risk. The empirical results we present suggest that 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. Investing 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, they demand compensation. An investment in large-growth firms instead provides some protection against creative-destruction risk.

Avenues for further research stretch in various directions. A consumption-based asset pricing model that accounts for cohort effects in consumption induced by the displacement effect and that uses invention activity as a scaling variable could help resolve the empirical weaknesses of the consumption-based asset pricing. To implement such a model, one could draw on the literature on asset pricing with heterogeneous agents and use the method proposed by Grishchenko and Rossi (2012) to allow for stochastic discount factors that differ across investor cohorts. To study the asset pricing implications of creative destruction at the firm level, time-varying firm characteristics could be accounted for by considering instruments/managed portfolios and scaled factors in a conditional asset pricing framework. Finally, a separation of patents that aim to protect extant businesses and those that are of potential destructive nature may help sharpen the analysis. We leave these topics for future research.

Appendix. Supplementary Material and Econometric Inference

A. Contents of the Internet Appendix

The Internet Appendix is a .zip file that consists, when unpacked, of three parts. There are two folders that contain programs, data, and explanations of how to use the programs (readme.txt). With the help of these programs, all reported results can be replicated. We provide the source code for GAUSS and MATLAB, both in separate folders. Any version

[18] Total population life expectancy in the United States, 2005. Source: *National Vital Statistics Reports*, 58 (Mar. 3, 2010).

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of GAUSS and MATLAB will work to run the programs on Windows or Linux systems. R-versions of the programs are available from the authors. In the third section of the Internet Appendix, we report the empirical results using equal-weighted size- and book-to-market-sorted portfolios, as well as the detailed results for the analyses described in Appendix Section C. The Internet Appendix is accessible at jfqa.org and also at tinyurl.com/JG-Research-Material.

B. GMM Inference for the Extended 2-Pass Regression Analysis

We treat the 2-pass regression approach toward estimating and testing a linear factor model like the CDRM as an instance of GMM, which amounts to collecting the moment conditions and their implicit weighting in the time-series and cross-sectional regressions. In Appendix Section B.1, we explain the methodological approach as it applies to the CDRM. We also show how to use the results of the 2-pass regression analysis to obtain statistical inference on the estimated risk compensations ($\hat{\beta}_i \times \hat{\lambda}$) and the estimates of the parameters of the model's SDF and covariance representation ($\hat{\gamma} = -\hat{b}$). In Appendix Section B.2, we turn to an extension that accounts for an initial estimation of the weights of a mimicking portfolio and that facilitates a convenient model specification test.

1. Estimation and Testing of the CDRM Using GMM for the 2-Pass Regression Analysis

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

$$\hat{\theta} : a_T(\theta) \times g_T(\theta) \quad \stackrel{!}{=} \quad 0, \tag{A-1}$$

where θ is a $(p \times 1)$ vector of parameters, and $g_T(\theta) = \frac{1}{T}\sum_{t=1}^{T} u_t(\theta)$. In turn $u_t(\theta)$ is a $(q \times 1)$ vector of random functions, such that $\mathbb{E}[u_t(\theta_0)] = 0$, where θ_0 denotes the true parameter vector, and $a_T(\theta)$ is of dimension $p \times q$, such that p linear combinations of $g_T(\theta)$ are set to 0.

For a 2-pass regression analysis of a linear M-factor model using the excess returns of K test assets, we set up

$$u_t(\theta) \quad = \quad \begin{bmatrix} \begin{bmatrix} r^e_{1,t} - a_1 - \beta_1' f_t \\ \vdots \\ r^e_{K,t} - a_K - \beta_K' f_t \end{bmatrix} \otimes \begin{bmatrix} 1 \\ f_t \end{bmatrix} \\ r^e_{1,t} - \beta_1' \lambda \\ \vdots \\ r^e_{K,t} - \beta_K' \lambda \end{bmatrix}, \tag{A-2}$$

where, for the CDRM, $M = 2$, $f_t = \left(r_{W,t}, pg_t\right)'$, $\beta_i = (\beta_{W,i}, \beta_{N,i})'$, and $\lambda = (\lambda_W, \lambda_N)'$. The parameter vector θ is thus given by $\theta = [a_1, \ldots, a_K, \beta_1', \ldots, \beta_K', \lambda_W, \lambda_N]'$. Furthermore, we use in equation (A-1):

$$a_T(\theta) \quad = \quad \begin{bmatrix} I_{3K} & 0_{3K \times K} \\ 0_{M \times 3K} & \beta \end{bmatrix}, \tag{A-3}$$

where $\beta = (\beta_1, \ldots, \beta_K)$, which, for the CDRM, reads:

$$\beta \quad = \quad \begin{bmatrix} \beta_{W,1} & \cdots & \beta_{W,K} \\ \beta_{N,1} & \cdots & \beta_{N,K} \end{bmatrix}. \tag{A-4}$$

Provided that $\hat{\theta} \underset{p}{\to} \theta_0$, we can use Hansen's (1982) celebrated formulas:

$$\sqrt{T}(\hat{\theta} - \theta_0) \quad \underset{d}{\to} \quad \mathcal{N}\left(0, [ad]^{-1} a S a' \left[[ad]^{-1}\right]'\right) \tag{A-5}$$

and

$$\sqrt{T}\, g_T(\hat{\theta}) \underset{d}{\rightarrow} \mathcal{N}\left(0, \left[I - d[ad]^{-1}a\right] S \left[I - d[ad]^{-1}a\right]'\right), \tag{A-6}$$

where $a_T(\hat{\theta}) \underset{p}{\rightarrow} a$, $S = \mathbb{E}[u_t(\theta_0) \cdot u_t(\theta_0)']$, and $d = \mathbb{E}[\frac{\partial u_t(\theta)}{\partial \theta'}\big|_{\theta_0}]$ (see Hansen (1982), thm. 3.1 and lem. 4.1).[19] For applied work, we use the estimates

$$\widehat{\text{var}}(\hat{\theta}) = \frac{[a_T(\hat{\theta})\hat{d}]^{-1} a_T(\hat{\theta}) \hat{S} a_T(\hat{\theta})' [a_T(\hat{\theta})\hat{d}]^{-1})'}{T} \tag{A-7}$$

and

$$\widehat{\text{var}}[g_T(\hat{\theta})] = \frac{\left[I - \hat{d}[a_T(\hat{\theta})\hat{d}]^{-1} a_T(\hat{\theta})\right] \hat{S} \left[I - \hat{d}[a_T(\hat{\theta})\hat{d}]^{-1} a_T(\hat{\theta})\right]'}{T}, \tag{A-8}$$

where

$$\hat{d} = \frac{\partial g_T(\theta)}{\partial \theta'}\bigg|_{\theta=\hat{\theta}} \quad \text{and} \quad \hat{S} = \frac{1}{T}\sum_{t=1}^{T} u_t(\hat{\theta}) u_t(\hat{\theta})'. \tag{A-9}$$

We get the t-statistics reported in Tables 3 and 4 by using $u_t(\hat{\theta})$ from equation (A-2) and $a_T(\hat{\theta})$ from equation (A-3) to compute $\widehat{\text{var}}(\hat{\theta})$ according to equation (A-7). We can then apply the delta method to obtain the limit distribution and variance of the risk-compensation estimates, in particular, $\hat{\beta}_{N,i} \times \hat{\lambda}_N$. The t-statistics reported in Table 5 are obtained in that way.

To compute the J-statistic in equation (16), we focus on the last K elements of $g_T(\hat{\theta}) = \frac{1}{T}\sum_{t=1}^{T} u_t(\hat{\theta})$ implied by equation (A-2). These are the average pricing errors for the K test assets, $\hat{\alpha} = (\hat{\alpha}_1, \ldots, \hat{\alpha}_K)'$ with generic element $\hat{\alpha}_i = \frac{1}{T}\sum r^e_{i,t} - \hat{\beta}_i'\hat{\lambda}$. Large positive or negative average pricing errors indicate model misspecification, and the J-statistic in equation (16) is used to test for significant deviations from 0. The matrix $\widehat{\text{var}}(\hat{\alpha})$ that is required for construction of the J-statistic is obtained from the intersection of the last K rows and columns of $\widehat{\text{var}}(g_T(\hat{\theta}))$ in equation (A-8). Under the null hypothesis that $\mathbb{E}[r^e_{i,t}] - \beta_i'\lambda = 0$, $\forall i$, it follows that J is approximately χ^2 distributed with degrees of freedom equal to K minus the number of factors (2, in the case of the CDRM). The J-test results reported in Table 4 are obtained in this way.

Drawing on equation (10), statistical inference on $\hat{\gamma} = \text{var}_T(f)^{-1}\hat{\lambda}$ can be based on the 2-pass regression results. Omitting time indices for convenience and using Hansen's (1982) notation, $\mathbb{E}_T(\cdot) = \frac{1}{T}\sum_{t=1}^{T}(\cdot)$; we write $\text{var}_T(f) = \mathbb{E}_T(\hat{f}\hat{f}')^{-1}$, where $\hat{f} = f - \mathbb{E}_T(f)$. By the continuous mapping theorem, we obtain $\mathbb{E}_T(\hat{f}\hat{f}')^{-1}\hat{\lambda} \underset{p}{\rightarrow} \mathbb{E}(f^* f^{*\prime})^{-1}\lambda_0 = \gamma_0$. Moreover, by the Slutzky theorem,

$$\begin{aligned}\sqrt{T}\left[\mathbb{E}_T(\hat{f}\hat{f}')^{-1}\hat{\lambda} - \mathbb{E}(f^* f^{*\prime})^{-1}\lambda_0\right] &= \sqrt{T}(\hat{\gamma} - \gamma_0) \\ &\underset{d}{\rightarrow} \mathcal{N}\left[0, \mathbb{E}(f^* f^{*\prime})^{-1}\text{Avar}(\hat{\lambda})\mathbb{E}(f^* f^{*\prime})^{-1}\right].\end{aligned}$$

Accordingly, we use

$$\widehat{\text{var}}(\hat{\gamma}) = \mathbb{E}_T(\hat{f}\hat{f}')^{-1}\widehat{\text{var}}(\hat{\lambda})\mathbb{E}_T(\hat{f}\hat{f}')^{-1} \tag{A-10}$$

to compute the t-statistics for $\widehat{\text{RRA}}$ and $\hat{\gamma}_N$ reported in Table 4, where $\widehat{\text{var}}(\hat{\lambda})$ is obtained from equation (A-7) (the intersection of the last two rows and columns of $\widehat{\text{var}}(\hat{\theta})$ in the case of the CDRM).

The GMM inference for a 2-pass regression analysis described here works in the same way for any other linear M-factor model (e.g., the CAPM and the Fama–French model).

[19] This assumes a serially uncorrelated $u_t(\theta_0)$ and that regularity conditions hold.

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2. GMM for the 2-Pass Regression Analysis with a Mimicking Portfolio: The Case of the MP-CDRM

We extend the GMM view toward the 2-pass regression analysis to account for the initial estimation of a mimicking portfolio and the computation of the cross-sectional and time-series estimates of $\lambda_{\tilde{N}}$. To be able to apply GMM, we collect the relevant moment conditions, which for the MP-CDRM imply the following:

$$u_t(\theta) = \begin{bmatrix} (pg_t - \psi_0 - \psi' r^e_{B,t}) \begin{bmatrix} 1 \\ r^e_{B,t} \end{bmatrix} \\ \psi' r^e_{B,t} - \lambda_{\tilde{N},ts} \\ \begin{bmatrix} r^e_{1,t} - \tilde{a}_1 - \tilde{\beta}'_1 \tilde{f}_t \\ \vdots \\ r^e_{K,t} - \tilde{a}_K - \tilde{\beta}'_K \tilde{f}_t \end{bmatrix} \otimes \begin{bmatrix} 1 \\ \tilde{f}_t \end{bmatrix} \\ r^e_{1,t} - \tilde{\beta}'_1 \tilde{\lambda} \\ \vdots \\ r^e_{K,t} - \tilde{\beta}'_K \tilde{\lambda} \end{bmatrix}, \tag{A-11}$$

where $\psi = (\psi_1, \ldots, \psi_6)'$, $\tilde{\beta}_i = (\beta_{W,i}, \beta_{\tilde{N},i})'$, and $\tilde{\lambda} = (\lambda_W, \lambda_{\tilde{N}})'$, such that $\theta = (\psi_0, \psi', \tilde{a}_1, \ldots, \tilde{a}_K, \tilde{\beta}'_1, \ldots, \tilde{\beta}'_K, \lambda_{\tilde{N},ts}, \lambda_W, \lambda_{\tilde{N},cs})'$. The vector $r^e_{B,t} = \left(r^e_{B,1,t}, \ldots, r^e_{B,6,t}\right)'$ contains the excess returns (here, that of the 6 Fama–French base assets), on which one of the factors (pg in the case of the MP-CDRM) is projected. Observe that $\tilde{f}_t = (r_{W,t}, \psi' r^e_{B,t})' = (r_{W,t}, r^e_{\tilde{N},t})'$. Furthermore, we use

$$a_T(\theta) = \begin{bmatrix} I_{3K+8} & 0_{3K+8\times K} \\ 0_{2\times 3K+8} & \tilde{\beta} \end{bmatrix}, \tag{A-12}$$

where

$$\tilde{\beta} = \begin{bmatrix} \beta_{W,1} & \cdots & \beta_{W,K} \\ \beta_{\tilde{N},1} & \cdots & \beta_{\tilde{N},K} \end{bmatrix}$$

for the generic GMM equation (A-1).

Using $u_t(\hat{\theta})$ from equation (A-11) and $a_T(\hat{\theta})$ from equation (A-12) to compute $\widehat{\text{var}}(\hat{\theta})$ in equation (A-7), we can obtain GMM inference on the beta and lambda estimates, as well as the risk-compensation estimates, in particular, $\hat{\beta}_{\tilde{N},i} \times \hat{\lambda}_{\tilde{N}}$ (using the delta method). The t-statistics reported for the MP-CDRM in Tables 3, 4, and 5 are computed in this fashion. Equation (A-7) provides an estimate of the variance–covariance matrix of all parameter estimates, such that the significance of the difference between cross-sectional and time-series estimates of $\lambda_{\tilde{N}}$ $\Delta\hat{\lambda} = \hat{\lambda}_{\tilde{N},cs} - \hat{\lambda}_{\tilde{N},ts}$ can be assessed using the Wald statistic $W_{\Delta\lambda}$ in equation (13). Moreover, we focus on the last K moment conditions implied by equation (A-11), the average pricing errors implied by the MP-CDRM, to construct a J-statistic similar to equation (16).

To obtain statistical inference on the estimates of γ_W and $\gamma_{\tilde{N}}$ in equation (12) based on the extended 2-pass regression results, we use

$$\hat{\tilde{\gamma}} = \begin{bmatrix} \hat{\gamma}_W \\ \hat{\gamma}_{\tilde{N}} \end{bmatrix} = \begin{bmatrix} -\hat{b}_W \\ -\hat{b}_{\tilde{N}} \end{bmatrix} = \text{var}_T(\tilde{f}_t)^{-1} \begin{bmatrix} \hat{\lambda}_W \\ \hat{\lambda}_{\tilde{N},cs} \end{bmatrix}, \tag{A-13}$$

and we proceed as described in the previous section to obtain $\widehat{\text{var}}(\hat{\tilde{\gamma}})$.

C. Bootstrap Simulation

To complement the GMM inference, we compute bootstrapped p-values for the t-statistics associated with the estimates of λ and γ, as well as the MAE from equation (14),

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and the cross-sectional coefficient of determination R^2_{cs} computed according to equation (15). The t-statistics are reported for the null hypothesis that the true parameter is 0; the null hypothesis for the p-values of the R^2_{cs} and the MAE is that the respective model has no explanatory power.

Following Maio and Santa-Clara (2012), we first draw with replacement a sample of length T (the sample size) from the risk factor data. To retain the contemporaneous dependence of the factors, we draw the factors simultaneously (i.e., one row of the matrix that contains the factor data). Second, we draw with replacement an *independent* sample of length T of the excess returns of the test assets. To retain the contemporaneous dependence of the excess returns, we draw them simultaneously (i.e., one row of the data matrix that contains the excess returns). Third, we apply the GMM procedures described in Appendix Section B to the simulated data, compute the t-statistics of the parameter estimates, and save them along with the R^2_{cs} and the MAE. The procedure is repeated $S=4,999$ times.

The reported p-values result from comparing the t-statistics, the MAE, and the R^2_{cs} obtained from the original sample with the S bootstrapped values. The p-values for the t-statistics are 2-sided and computed as the relative frequency of bootstrapped t-statistics that are, in absolute terms, larger than the t-statistic based on the real data. The p-values for the R^2_{cs} and the MAE are 1-sided. The null hypothesis of no explanatory power would be rejected for large R^2_{cs} and small MAE, respectively. Accordingly, the relative frequency of simulations, for which the R^2_{cs} is greater than the R^2_{cs} obtained from the original data, gives the p-value for the R^2_{cs}. Similarly, the p-value for the MAE is the relative frequency of simulations, for which the MAE is smaller than the MAE obtained from the original data.

D. 2-Pass Regression, SDF-Based GMM Estimation, and Covariance-Based GMM Estimation: Equivalence and Inference

Equation (10) holds true for any linear factor model, for example, the CAPM, CDRM, Fama–French model, or MP-CDRM (see equation (A-13)). The result can be shown as follows. Consider the multiple-beta representation $\mathbb{E}[r^e_{i,t}]=\beta_i'\lambda$ of an M-factor model with $f_t=(f_{1,t},\ldots,f_{M,t})'$, where $\beta_i=\mathbb{E}[f_t^* f_t^{*\prime}]^{-1}\mathbb{E}[f_t^* r^e_{i,t}]$, $f_t^*=(f_t-\mu_f)$, and $\mu_f=\mathbb{E}(f_t)$. Cochrane (1996) notes that the parameters of the covariance representation

$$\text{(A-14)}\qquad \mathbb{E}[r^e_{i,t}] \;=\; \gamma'\mathrm{cov}(f_t,r^e_{i,t}) \;=\; \gamma'\mathbb{E}[(f_t-\mu_f)\cdot r^e_{i,t}],$$

and the parameters of the SDF representation,

$$\text{(A-15)}\qquad \mathbb{E}[m_t\cdot r^e_{i,t}] \;=\; 0,$$

where $m_t=1+b'f_t^*$,[20] are related such that $b=-\gamma=-\mathbb{E}(f_t^* f_t^{*\prime})^{-1}\lambda$.

Using data on K excess returns $r^e_{i,t}=(r^e_{1,t},\ldots,r^e_{K,t})'$, a 2-pass regression analysis delivers estimates of β_i, $i=1,\ldots,K$ and λ via:

$$\text{(A-16)}\qquad \hat\beta \;=\; (\hat\beta_1,\ldots,\hat\beta_K)' \;=\; \mathbb{E}_T(\hat f\hat f')^{-1}\mathbb{E}_T(\hat f r^{e\prime}),$$

$$\text{(A-17)}\qquad \hat\lambda \;=\; [\hat\beta\hat\beta']^{-1}\hat\beta\,\mathbb{E}_T(r^e).$$

For notational convenience, we omit time indices and use $\mathbb{E}_T(\cdot)=\frac{1}{T}\sum_{t=1}^{T}(\cdot)$. Maio and Santa-Clara (2012) estimate γ by drawing on the moment conditions implied by the covariance representation in equation (A-14) and using the following moment matches for GMM:

$$\text{(A-18)}\qquad g_T(\gamma,\mu_f) \;=\; \begin{bmatrix}\mathbb{E}_T(r^e)-\mathbb{E}_T[r^e(f-\mu_f)']\gamma\\ \mathbb{E}_T(f)-\mu_f\end{bmatrix}.$$

[20] As suggested by Cochrane (1996), factor means are "folded" into the intercept in m, which is set to 1 to ensure identification.

Minimizing the GMM objective function $g_T(\gamma,\mu_f)'Wg_T(\gamma,\mu_f)$ implies that μ_f, and thus the covariances of factors and excess returns, $\mathbb{E}[(f-\mu_f)r_i^e]$, are not exactly matched by sample moments. However, obtaining the parameter estimates by solving the generic GMM in equation (A-1), which in the present case reads

$$(\text{A-19}) \qquad (\hat{\gamma},\hat{\mu}_f)' \quad : \quad \begin{bmatrix} \mathbb{E}_T(f-\mu_f)r^{e\prime} & 0_{M\times M} \\ 0_{M\times K} & I_M \end{bmatrix} \times g_T(\gamma,\mu_f) \quad \stackrel{!}{=} \quad 0,$$

forces the matching of population moments by sample means, $\hat{\mu}_f = \mathbb{E}_T(f)$. The estimates $\hat{\gamma}$ then fulfill:

$$(\text{A-20}) \qquad \mathbb{E}_T(\hat{f}r^{e\prime}) \times \left[\mathbb{E}_T(r^e) - \mathbb{E}_T(r^e\hat{f}')\hat{\gamma}\right] \quad = \quad 0.$$

Pre-multiplying by $\mathbb{E}_T(\hat{f}\hat{f}')^{-1}$ and rearranging terms, we obtain:

$$(\text{A-21}) \qquad \begin{aligned} \hat{\beta}\mathbb{E}_T(r^e) &= \hat{\beta}\mathbb{E}_T(r^e\hat{f}')\mathbb{E}_T(\hat{f}\hat{f}')^{-1}\mathbb{E}_T(\hat{f}\hat{f}')\hat{\gamma} \\ &= \hat{\beta}\hat{\beta}'\mathbb{E}_T(\hat{f}\hat{f}')\hat{\gamma}. \end{aligned}$$

Solving for $\hat{\gamma}$ reveals the relation to the cross-sectional regression slopes $\hat{\lambda}$:

$$(\text{A-22}) \qquad \hat{\gamma} \quad = \quad \mathbb{E}_T(\hat{f}\hat{f}')^{-1}[\hat{\beta}\hat{\beta}']^{-1}\hat{\beta}\mathbb{E}_T(r^e) \quad = \quad \mathbb{E}_T(\hat{f}\hat{f}')^{-1}\hat{\lambda}.$$

For a first-stage GMM estimation of the parameter vector b based on the moment conditions implied by the SDF representation in equation (A-15), we use

$$(\text{A-23}) \qquad g_T(b) \quad = \quad \begin{bmatrix} \mathbb{E}_T(1+b'\hat{f})r_1^e \\ \vdots \\ \mathbb{E}_T(1+b'\hat{f})r_K^e \end{bmatrix},$$

and we obtain $\hat{b}$ by minimizing the GMM objective function $g_T(b)'I_K g_T(b)$. The first-order conditions of the optimization problem read $\frac{\partial g_T}{\partial b}' g_T(b) \stackrel{!}{=} 0$, such that $\hat{b}$ has to fulfill:

$$(\text{A-24}) \qquad \mathbb{E}_T(\hat{f}r^{e\prime}) \times \left[\mathbb{E}_T[r^e] + \mathbb{E}_T[r^e\hat{f}']\hat{b}\right] \quad = \quad 0.$$

Noting the similarity to equation (A-20), we proceed as before when solving for $\hat{b}$, which proves equation (10):

$$(\text{A-25}) \qquad \begin{aligned} \hat{b} &= -\mathbb{E}_T(\hat{f}\hat{f}')^{-1}[\hat{\beta}\hat{\beta}']^{-1}\hat{\beta}\mathbb{E}_T(r^e) \\ &= -\mathbb{E}_T(\hat{f}\hat{f}')^{-1}\hat{\lambda} \quad = \quad -\hat{\gamma}. \end{aligned}$$

Using equation (A-25), it can easily be shown that the average pricing errors implied by the three approaches are identical:

$$(\text{A-26}) \qquad \begin{aligned} \alpha(\hat{\beta},\hat{\lambda}) &= \mathbb{E}_T[r^e] - \hat{\beta}'\hat{\lambda} \quad = \quad \alpha(\hat{b}) \\ &= \mathbb{E}_T[r^e] + \mathbb{E}_T[r^e\hat{f}']\hat{b} \quad = \quad \alpha(\hat{\gamma}) \\ &= \mathbb{E}_T(r^e) - \mathbb{E}_T(r^e\hat{f}')\hat{\gamma}. \end{aligned}$$

The 2-pass regression analysis (implicitly) and the GMM estimation of $\hat{\gamma}$ as described earlier (explicitly) treat the factor means in μ_f as parameters to be estimated. Conversely, SDF-based GMM estimation of b according to Cochrane (1996) starts with de-meaned factors and thus does not account for estimation uncertainty regarding μ_f. As a result,

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the variance–covariance matrixes of the (implied) parameter estimates and average pricing errors and the statistics derived from them will differ in a finite sample. In particular, the value of the SDF-moments-based J-statistic will differ from the value of the J-statistic for the 2-pass regression analysis and the covariance-based GMM estimation.[21]

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