Factor Contamination and Displacement Risk in International Asset Pricing

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January 15, 2026

Abstract

This paper links equity returns to the threat of displacement in global product-market competition by developing a model with heterogeneous firms under imperfect competition. Supply-side shocks contaminate global single-factor proxies for the stochastic discount factor. The model therefore identifies global factors to correct for factor contamination while pricing displacement risk. Using data for 64,740 stocks from 55 economies, I find that a conditional multifactor model successfully explains the global cross-section of excess stock returns for developed-economy-industry portfolios with a Hansen-Jagannathan metric of 0.032. Unlike unconditional models, the conditional multifactor model delivers consistent performance during both normal and displacement periods.

Key words: Equity Returns, Imperfect Competition, Currency Risk, Technology, Tariffs.

JEL Classification: F12 (International Trade), G12 (Cross-Sectional Asset Pricing), G15 (International Financial Markets).

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1. Introduction and Related Literature

The notion that a single market factor can price all international stocks is elegant in its simplicity. Yet the world capital asset pricing model (CAPM) consistently fails to explain the cross-section of global equity returns. This failure has fueled a search for a more structural, economically coherent, and multidimensional understanding of international asset pricing (Lewis, 2011). I show that the source of the failure is hidden within the market factor itself: it conflates systematic risk with competitive forces in global product markets.

The purpose of this paper is to explain global equity risk premia by building a unified theoretical and empirical framework rooted in international trade and competition. By investigating the equity risk premia of heterogeneous firms that operate and compete globally, this paper sits at the intersection of three research areas: international trade, industrial organization, and asset pricing. In an international asset pricing model, investors pay a premium for assets that insure against risks embedded in a global stochastic discount factor (SDF).

Drawing on insights from international trade and industrial organization (IO),[1] I show that product-market competition creates displacement risk: the risk that firms lose market share or are completely displaced by more productive rivals through price competition. This displacement activity generates factor contamination: single-factor SDF proxies are contaminated because they are endogenous mixtures of aggregate economic shocks and displacement-driven reallocation,

[1] The trade-IO literature has a long and rich history, beginning with Krugman's (1979, 1980) incorporation of imperfect competition into trade theory and accelerating with Melitz's (2003) introduction of firm heterogeneity. Much of this work centers on how firms with differing productivities, markups, and cost structures compete for market share across borders, often displacing weaker rivals. These competitive dynamics determine which firms expand, contract, or exit, thereby shaping the distribution of profits and exposure to economic shocks.

conflating exposure to systematic risk with exposure to competitive displacement.[2] In this environment, no single factor can separately price displacement risk.

The market factor presents a prime illustration of factor contamination. While the empirical failure of the CAPM is well documented, the economic roots of that failure remain obscure. This paper shows that the world market factor is fundamentally contaminated because it emerges as an endogenous outcome of competition. When dominant firms displace vulnerable rivals in product markets, the value-weighted market factor assigns too much weight to the winners and too little to the losers, causing the market factor to overweight the cash flows and returns of dominant firms. While value-weighting exacerbates the contamination, equal-weighting does not eliminate it.[3] Consequently, the world CAPM cannot simultaneously price the vulnerable firms displaced by competition and the dominant firms enriched by it.[4] Vulnerable firms may even show an inverse relation with the contaminated market factor, producing negative betas that violate the CAPM's core prediction: their stock prices fall precisely when displacement by dominant firms drives the market index upward. Section B.1 in Appendix B provides an accessible explanation of why single-factor models like the world CAPM fail in the presence of competitive displacement.

To address this empirical failure in international asset pricing, I develop a general equilibrium model with heterogeneous firms under imperfect competition. Many asset-pricing

[2] Related econometric issues arise when observed factors are noisy proxy variables for the true pricing kernel (Kleibergen and Zhan, 2015; Lettau and Pelger, 2020).

[3] This paper's model shows that an equal-weighted market index exhibits less severe contamination than the value-weighted index, consistent with improved performance of alternative weighting schemes (Arnott, Hsu, and Moore, 2005; Plyakha, Uppal, and Vilkov, 2015). However, equal weighting does not eliminate the problem, suggesting that factor contamination reflects the underlying competitive displacement mechanism rather than the weighting choice alone.

[4] This mechanism provides a structural explanation for the low-beta anomaly (Black, 1972): Vulnerable firms exhibit low (or negative) betas because their cash flows covary inversely with a market factor driven by dominant firms during competitive reallocation, yet these vulnerable firms earn high returns due to displacement risk. Existing explanations for the low-beta anomaly focus on leverage constraints (Frazzini and Pedersen, 2014) or limits to arbitrage (Baker, Bradley, and Wurgler, 2011), but these institutional explanations do not fully address why the anomaly is particularly pronounced among small, vulnerable firms facing competitive displacement.

models implicitly hold supply-side conditions fixed, with uncertainty driven by demand-side fluctuations in aggregate consumption, so relative costs and market shares remain unchanged. However, displacement is fundamentally a supply-side phenomenon: when relative costs change due to supply-side shocks, firms lose market share to rivals that can charge lower prices. As a result, this displacement mechanism generates factor contamination endogenously when I apply both demand-side income shocks and supply-side cost shocks to a Ricardian equilibrium under strong comparative advantage.

The model is used to identify firms that are most affected by factor contamination, as evidenced by their negative or noisy market betas. Firms exhibiting those betas tend to be smaller and less profitable relative to competitors. These firm-level characteristics are also associated with greater expected excess equity returns precisely when market betas are negative or noisy. While the size result is consistent with existing empirical evidence, the result surrounding relative profitability is novel and distinct in its empirical pattern. Unlike firm size, which exhibits a linear relation with expected excess returns, relative profitability exhibits an extreme nonlinearity near displacement: expected excess equity returns rise sharply as relative profits approach zero.

Monthly data for 64,740 stocks from 55 economies between July 1989 and June 2024, reveal a similar pattern: global equity portfolios sorted on industry-adjusted return on equity (ROE) exhibit a nonlinear relation to excess returns, showing a sharp increase for the least profitable firms at risk of displacement. Hence equity risk premia for the most vulnerable firms reflect the extreme nonlinearity near displacement emphasized by the theory. The IAROE factor, constructed as the long-short portfolio of the lowest relative profitability quintile minus the next quintile, delivers a mean monthly excess return of 0.804% (9.65% annualized) with an annualized Sharpe ratio of 1.123.

Evidence of factor contamination appears when using diagnostic time-series regressions that isolate competitive displacement between small and large firms and within industries. First, a global long–short size portfolio (small minus big) has a *negative* exposure to the global market factor in a single-factor regression.[5] However, this paper's six factors (global market, GMKT; firm size, SIZE; IAROE; technology, TECH; trade protection, TDPRT; and currency risk, CRX) substantially reduce both the alpha and the absolute market beta compared to the single-factor regression. In comparison, the five world Fama-French factors do not materially change these statistics (see Panel A of Table B.8 in Appendix B).

Second, a long–short profitability dispersion portfolio (i.e., global sorts on the industry interquartile range of return on equity; high minus low dispersion) earns a significant alpha in a single-factor regression, suggesting that competitive forces within industries are systematically mispriced by contaminated single-factor models. The alpha becomes insignificant once the six factors are included, while the five world Fama-French factors provide no remedy. In fact, the monthly alpha for industry profitability dispersion increases from roughly 0.45% to 0.65% when the five factors are included (see Panel B of Table B.8 in Appendix B).

Although these anomaly diagnostics are consistent with factor contamination arising from competitive displacement, they do not by themselves distinguish contamination from a simpler story of state-invariant omitted displacement risk. Nevertheless, under the world CAPM assumption of a constant market beta, factor contamination makes a stronger claim using state dependence. If an endogenous market proxy embeds displacement interactions, then estimated market betas for displacement-sensitive portfolios are subject to a systematic bias that intensifies

[5] A negative market beta for the global small-minus-big portfolio, while seemingly puzzling under the world CAPM, is not uncommon in global equity data. This contrarian pattern extends to 20 global Fama-French portfolios sorted on size and operating profitability. Figure B.6 in Appendix B shows that mean market betas correlate negatively with average excess returns, revealing a pointed manifestation of the low-beta anomaly (see fn. 4).

in states where displacement is most severe.[6] Using conditioning instruments based on TECH and TDPRT, I identify six episodes of severe displacement within the sample period. During these episodes, market betas for the long–short profitability dispersion portfolio shift materially relative to normal periods. Once all six factors are included, this instability disappears: the market beta stabilizes across regimes, while exposure to IAROE rises precisely during displacement periods. Appendix B explores the robustness of these results by investigating whether they reflect a generic state-dependent omitted factor, or instead factor contamination arising from competitive displacement and amplified by value-weighting the market factor.

Guided by the theoretical structure and consistent with the empirical evidence, I develop a conditional world multifactor model that successfully explains the global cross-section of excess stock returns. The world multifactor model is constructed using a conditional generalized method of moments (GMM) estimator (specified in terms of conditional moment restrictions). This paper's world multifactor model exhibits better cross-sectional fit compared to the world CAPM benchmark model when using economy–industry portfolios, both globally and for developed markets only.[7] It also achieves a better fit than the world Fama-French five-factor model.[8]

[6] The sign of the contamination bias depends on the portfolio's displacement sensitivity. For example, the predicted sign of the bias for the long–short profitability dispersion portfolio is positive: displacement episodes shift value-weighted market returns toward high-profitability winners and away from low-profitability losers, causing the observed market proxy to covary positively with the portfolio's payoff. In contrast, displacement-vulnerable portfolios are predicted to exhibit downward-biased market betas. Factor contamination differs from a simple state-invariant omitted-variable interpretation. Standard state-invariant omitted variable logic implies persistent pricing errors (alphas) when a risk factor is excluded, but does not predict that estimated market betas should exhibit state-dependent instability that disappears and reassigns to the omitted factor once that factor is included.

[7] I use economy-industry portfolios as test assets for two reasons: first, these portfolios are not constructed from sorts that mimic the model's factors, avoiding the common criticism that test assets are chosen to favor the model; second, the portfolios align naturally with the model's competitive structure, where firms compete internationally within industries.

[8] I benchmark the model primarily against the world CAPM rather than the world Fama-French five-factor model (FF5) because the FF5 is not an integrated global model, thus underperforms when test assets include both developed and emerging markets. Nevertheless, the multifactor model also achieves a better cross-sectional fit compared to the world Fama-French five-factor (FF5) model on its own terms (developed markets only).

The world multifactor model uses three principal components derived from functions of the economy-based factors (TECH and TDPRT) as conditioning instruments. Analysis of structural breaks in the conditioning instruments identifies six episodes of severe competitive disruption (e.g., trade collapse following the 2008-09 global financial crisis, 2018 US-China trade war) that occur during "displacement periods." Imposing moment orthogonality on these instruments yields a conditional Hansen–Jagannathan metric of 0.032 for developed-economy-industry portfolios, indicating that very little systematic pricing error remains once competitive conditions are allowed to vary over time.

To illustrate the practical meaning of this performance, I examine cross-sectional pricing errors across the six displacement episodes. Using residuals from cross-sectional regressions of expected returns on mean model-implied betas, the world multifactor model delivers a low mean absolute pricing error (MAPE) during normal periods and maintains essentially the same MAPE during displacement periods. While the world multifactor model maintains consistent performance during both normal periods and displacement periods, leading unconditional models like the world CAPM deteriorate precisely when displacement is most severe. This deterioration is concentrated in test assets with high within-industry profitability dispersion where competitive reallocation is most severe, confirming that the multifactor model's superior conditional performance stems from correctly pricing displacement risk that contaminates traditional factors. These empirical results demonstrate a substantial improvement in both pricing performance and model stability.

To provide a structural foundation for these empirical results, this paper's theoretical model builds on the Ricardian framework of Eaton and Kortum (2002; or EK) and Bernard et al. (2003; or BEJK). I extend EK and BEJK by using a dynamic setting with trade shocks and complete

markets, where individuals can fully insure against all possible risks.[9] Ricardian trade theory shows that economies benefit from specialization based on relative efficiency (i.e., a comparative advantage), even when one economy can produce all goods more efficiently than the others (i.e., has an absolute advantage). BEJK introduce imperfect competition through Bertrand pricing, where lower-cost firms price just below their rivals.

Under Bertrand competition, the lowest-cost supplier to each market sets its price constrained by the second-lowest cost, generating variable markups that increase with a firm's efficiency advantage over its rivals. Hence, the most efficient producers charge higher markups and are more likely to overcome geographic barriers and export to foreign markets. This competitive structure is a natural backdrop for studying how cost changes affect market shares and displacement risk.

EK and BEJK both use a probabilistic approach to determine the likelihood that a source economy is the lowest cost supplier of each individual good to every destination economy. Specifically, π_{ni} is the probability that source economy i sells a good to destination economy n. Both models aggregate these individual sourcing probabilities across all goods via the law of large numbers, incorporating economy-level production and bilateral trade costs to generate a structural gravity equation that explains trade between two economies.[10]

[9] Log utility and complete markets are modeling choices that allow for tractability when studying heterogeneous firms under imperfect competition. Specifically, complete markets isolate real competitive forces from financial frictions. The core distinction is between hedging aggregate states (which complete markets provide) and pricing systematic redistribution within those states (which generates risk premia regardless). Displacement risk is systematic because supply-side shocks create correlated firm-value movements that covary with the SDF. A key finding of this paper's model is qualitative: In the presence of supply-side shocks, many firms exhibit contrarian SDF exposures—a phenomenon absent from traditional single-factor models. This qualitative pattern emerges from competitive displacement, not from the utility specification. Appendix C.6 discusses why displacement risk is priced under complete markets.

[10] The gravity equation establishes that bilateral trade shares vary systematically, increasing with the source economy's production and the destination economy's expenditure, but decreasing with geographic and trade barriers between the two economies. In EK, general equilibrium is achieved through endogenous adjustment of manufacturing employment and sourcing patterns given exogenous wage costs on the supply side and exogenous endowment incomes on the demand side. Constant elasticity of substitution (CES) preferences determine how consumers allocate income by

While I follow EK and BEJK's probabilistic approach for aggregate consumption, I explicitly simulate firm-level competition in destination markets rather than relying on distributional assumptions. Trade shocks therefore affect firm profits and equity returns directly.[11] At the firm level, the model generates profits and profit growth, which are mapped into equity returns using a simulated method of moments (SMM) exercise.

The SMM exercise matches four sample moments of global stock returns for developed economies: the mean, median, standard deviation, and skewness. The results of the SMM exercise reveal a key finding: supply-side shocks are required to generate the skewness observed in global equity returns. Demand-side shocks alone produce symmetric return distributions with limited dispersion and cannot account for higher-order moments. Supply-side shocks generate the necessary asymmetry.

Supply-side shocks do more than generate realistic return distributions; they fundamentally undermine single-factor pricing models. When only demand-side shocks are present, expected excess returns align with exposure to canonical SDFs such as the world market return or global consumption growth, consistent with the world CAPM and CCAPM. Once supply-side shocks are introduced, however, this correspondence breaks down.

Cost shocks alter relative competitiveness across firms, allowing displacement to occur with some firms experiencing returns of –100% (complete displacement and exit). As a result, many firms exhibit negative or noisy market betas under the value-weighted world market return

purchasing from suppliers that deliver the lowest costs. In equilibrium, a source economy's aggregate consumption increases with its export performance across all destinations.

[11] Trade shocks are exogenous, unpredictable changes that affect the net gain or loss from trade. Demand-side examples include a trade partner's economic boom due to valuable natural resource discoveries. Supply-side examples include transportation cost increases from fuel price shocks or labor disruptions that raise production costs. Trade shocks can be global and pervasive (Liu, Ornelas, and Shi, 2022), or bilateral and isolated, and may be limited to specific product sectors. Terms-of-trade shocks can significantly impact economies (Schmitt-Grohé and Uribe, 2018) and individual firms within them (Greenland et al., 2024).

SDF, and positive but similarly noisy exposures under the global consumption growth SDF. Traditional single-factor SDFs thus become unreliable when supply-side shocks drive reallocation and displacement.

The failure of traditional single-factor SDFs under supply-side shocks raises the question of how to correct for factor contamination in this setting. While an analytical solution would ideally characterize the precise functional form of the correct SDF, no such solution exists. Therefore, I use the model itself as a laboratory: a logit regression on simulated firms links negative or noisy market betas to firm-level and economy-level characteristics. In effect, this exercise isolates the firms most susceptible to factor contamination.

Firms with negative or noisy market betas tend to be smaller and less profitable relative to competitors, and are more likely to be located in economies with greater absolute advantage, weaker trade protection, and lower currency risk. This systematic predictability implies that CAPM failures arise from structural features of competition rather than random noise. A single global market factor is therefore insufficient, which provides a theoretical rationale for a multifactor model of international asset pricing.

To translate these findings into the design of an empirical multifactor model of international asset pricing, I follow a structured approach based on the economic role each characteristic plays. First, I determine which characteristics represent systematic risks that investors cannot diversify away. Competitive displacement risk is pervasive, with investors unable to simultaneously avoid exposure to dominant and vulnerable firms in global product markets. Therefore, I incorporate factor-mimicking portfolios for the two firm-level characteristics (size and relative profitability) as priced factors. I likewise treat currency risk as a priced factor,

consistent with theoretical and empirical work showing that currency risk premia compensate for global risk exposures.

Absolute advantage (i.e., the state of technology) and trade protection are poor candidates for priced factors.[12] These variables function more naturally as controls that inform how competitive displacement risk is transmitted across economies, not as independent risks that earn compensation. Accordingly, I construct factor-mimicking portfolios for these characteristics and use them as the basis for instruments in a conditional GMM framework.[13]

This paper ties together international asset pricing and IO-finance research. International asset-pricing models extending the CAPM to open economies (Solnik, 1974; Stulz, 1981; Adler and Dumas, 1983) show that excess equity returns depend on global risk factor exposures, with subsequent work demonstrating that conditional versions improve performance (Harvey, 1991; De Santis and Gérard, 1997, 1998) and that factor premiums exist internationally (Fama and French, 2012, 2017). However, these approaches leave real-economy mechanisms unspecified. Meanwhile, IO-finance research shows that competition affects excess equity returns (Hou and Robinson, 2006; Loualiche, 2021; Barrot, Loualiche, and Sauvagnat, 2019; Fillat and Garetto, 2015), but these frameworks remain focused on a single economy (the US) and do not model cross-border competitive displacement in global general equilibrium.

This paper shows that competitive displacement in global product markets is a central determinant of international equity risk premia and develops a unified theoretical and empirical

[12] Macro and economy-level variables often exhibit weak correlation with returns (Kroencke, 2017), suffer from weak identification (Kleibergen and Zhan, 2020; Cheng, Dou, and Liao, 2022), and may behave as spurious factors rather than true sources of systematic risk (Kan and Zhang, 1999; Gospodinov, Kan, and Robotti, 2014).

[13] The economy-based factors do not earn risk premia; instead, they condition estimation by purifying the market factor of contamination arising from cross-economy heterogeneity. This treatment reflects an important distinction between priced risks and conditioning variables that aligns econometric identification with economic intent. Specifically, firm-level characteristics linked to displacement serve as a basis for priced factors, while economy-level variables serve as a basis for instruments that help recover the correct global prices of risk.

framework to analyze it. By doing so, the paper makes four important contributions: First, it provides a structural explanation for why global single-factor models like the world CAPM fail in the presence of competitive displacement by clarifying the role of factor contamination. Second, the paper offers new empirical evidence on the pricing of displacement risk, including the essential-singularity pattern in returns and the discovery of a novel IAROE factor.[14] Third, it develops a formal testing framework that distinguishes factor contamination from generic omitted-variable bias. Fourth, the paper develops and estimates a conditional world multifactor model that corrects for factor contamination. Together, these results demonstrate that displacement risk is a fundamental component of global equity premia and that accounting for factor contamination is essential for building coherent models of international asset pricing.

2. A Ricardian Model of International Asset Pricing

To clarify the theoretical role of imperfect global competition in international stock returns, I begin with a model where all the fundamental ingredients are derived from a single Ricardian model of international trade. This paper uses the modelling structure of Eaton and Kortum (2002; or EK) and Bernard et al.(2003; or BEJK). In both models, there is a continuum of goods that are traded under diverse states of technology in multiple economies. EK use a probabilistic approach to model heterogeneous firms with a particular focus on economy-level outcomes. BEJK extend the EK model to capture imperfect global competition. This paper's model also extends the EK model by capturing imperfect global competition, but does so using an *explicit* approach within a multiperiod framework. The model allows for a characterization of both economy-level outcomes (e.g., consumption growth) and explicit firm-level outcomes (e.g., stock returns) in the presence of simultaneous supply-side and demand-side shocks. Sections 2.1 and 2.2 introduce the model

[14] Appendix B discusses the qualitative and quantitative differences between IAROE and RMW.

environment. Section 2.3 examines how firm-level profits translate to stock returns. Section 2.4 explores how isolated demand-side trade shocks affect equity risk premia before developing the full model, in which supply-side and demand-side shocks operate simultaneously.

2.1 Model Structure and Assumptions

Consider a Ricardian model with three dates t = 0, 1, 2. In the initial transactional period (t = 0), financial market completeness allows for trade in a complete set of Arrow-Debreu claims.[15] In the following trading period (t = 1), explicit firm-level profits and stock returns are determined through imperfect competition (similar to BEJK) while economy-level outcomes are determined within a probabilistic equilibrium (similar to EK).

Appendix C shows the main elements of the model at time t = 1. The time-invariant state of technology in economy i is $T_i > 0$ (i.e., its absolute advantage), while the global (i.e., economy-time-invariant) prevalence of comparative advantage in international trade is $\theta > 0$. A lower θ indicates stronger comparative advantage forces relative to geographic barriers. The input cost in source economy i at time t = 1 is $c_{i,1}$, which incorporates both wages and input costs from intermediate goods. In every source economy, each good j is assigned to its most efficient domestic firm, and no firm produces more than one good. A firm k can convert one bundle of inputs into a quantity $z_{ki,1}(j)$ of good j at constant returns to scale. Hence, the cost for firm k of producing a unit of good j in economy i at time t = 1 is $c_{i,1}/z_{ki,1}(j) = c_{ki,1}$. Destination economy n is eventually supplied by the lowest-cost firm with a price set to the cost for the firm with the second lowest cost, leading to a markup of $U_{kn,1}$ in economy n. The firm that supplies a good in economy n earns $x_{kn,1}$ in revenue while experiencing a cost of $V_{kn,1} = x_{kn,1}/U_{kn,1}$. The total profit for a firm is the sum of all of the profits it earns in the different markets it supplies.

[15] See fn. 9.

In the final period (t = 2), each firm experiences stochastic shocks which engender a new profit equilibrium as well as its stock return.

2.2 Heterogeneity in Trade Shocks

At time $t = 2$, a firm k in economy i may experience supply-side stochastic shocks to its exporting costs ($H^{s}_{ki,2}$) or demand-side stochastic shocks to trade-partner incomes ($H^{d}_{kn,2}$). These trade shocks can have local, global, and firm-specific sources. Global trade shocks can be homogeneous in affecting all goods equally, or they can be heterogeneous and good-specific.[16] There are four separate shocks for the supply side and the demand side.

[1] $$H^{s}_{ki,2} = 1 + \kappa_s\left(\zeta_{k,i,2} + \varepsilon_{i,2} + \eta_{g,2} + \nu_{j,g,2}\right)$$

[2] $$H^{d}_{kn,2} = 1 - \kappa_d\left(\zeta_{k,n,2} + \varepsilon_{n,2} + \eta_{g,2} + \nu_{j,g,2}\right)$$

In [1] and [2], the following shocks are all standard normal variables: firm-specific shocks for source economy i ($\zeta_{k,i,2}$) and destination economy n ($\zeta_{k,n,2}$), local shocks for source economy i ($\varepsilon_{i,2}$) and destination economy n ($\varepsilon_{n,2}$), heterogeneous global shocks $\nu_{j,g,2}$, and homogeneous global shocks $\eta_{g,2}$. κ_s is a scaling factor on the supply side, while κ_d is a scaling factor on the demand side. I assume that firm-specific shocks, local shocks and global shocks are uncorrelated with each other; but homogeneous global shocks are correlated with heterogeneous global shocks. Heterogeneous global shocks $\nu_{j,g,2}$ represent global shocks to specific goods or sectors (good j).[17]

[3] $$corr\left(\eta_{g,2}, \nu_{j,g,2}\right) = \rho_{\eta\nu}$$

2.3 Firm-Level Profits and Stock Returns Within Ricardian Trade

Appendix C presents the explicit equilibrium profits for a firm k from economy i at time $t = 1$ as

[16] These heterogenous shocks share some similarities with the sectoral shocks in the real business cycle literature (Long and Plosser, 1987; Horvath, 2000).

[17] These heterogeneous shocks affect source economy i only when it produces goods in the affected sectors.

$\Pi_{ki,1}$. The equation is reproduced in [4] where $x_{kn,1}$ is the revenue firm k earns in economy n at time t = 1, and $V_{kn,1}$ is the total production cost for firm k in economy n at time t = 1. $\Lambda_{ki,1}$ is the set of served markets for firm k from economy i at time t = 1.

[4] $$\Pi_{ki,1} = \sum_{n\in\Lambda_{ki,1}} x_{kn,1} - V_{kn,1}$$

This paper's Ricardian model can characterize stock returns in the presence of trade shocks. I assume that there are no trade shocks at time t = 1. However, in characterizing the stock return for a firm k at time t = 2, exporter costs and the spending on good j change from time t = 1 to time t = 2 only because of shocks.[18]

[5] $$c_{ki,t} = \left[c_{i,1}/z_{ki,1}(j)\right]^{\varrho}\left(H^{s}_{ki,t}\left[c_{i,1}/z_{ki,1}(j)\right]\right)^{1-\varrho}$$

$$= {c_{ki,1}}^{\varrho}\left(H^{s}_{ki,t}c_{ki,1}\right)^{1-\varrho}$$

[6] $$x_{kn,t} = H^{d}_{kn,t}x_{kn,1}$$

Given the explicit representation for profits in [4], the stock return for firm k at time t = 2 is a function of $c_{ki,2}$ and $x_{kn,2}$. This stock return $\mathrm{R}_{ki,2}$ can be represented by the following Gordon dividend growth equation.

[7] $$\mathrm{R}_{ki,2} = \delta\frac{\Pi_{ki,2}}{2\sum_{n\in\Lambda_{ki,1}} x_{kn,1}} + \frac{\Pi_{ki,2}-\Pi_{ki,1}}{\Pi_{ki,1}}$$

In [7], the first term is the dividend yield where δ is the ratio of dividends to operating profits while the equity-to-sales ratio is assumed to be 2 for all firms. The second term in [7] is the profit growth rate. I use a simulated method of moments (SMM) approach to estimate the necessary parameters for generating stock returns in [7]. Section C.4 in Appendix C presents the details of

[18] For modeling convenience, I introduce a reduced-form shock $H^{s}_{ki,t}$ to $c_{ki,1}$, which in this setup corresponds to a shock to the exogenous wage. This shock operates qualitatively like a bundle cost shifter, with an adjustment to endogenous prices. Interpreted structurally, a wage shock is transmitted with intensity given by the intermediate share $1-\beta_p$. Equivalently, for small shocks one can express this bundle shock as a wage-only shock. This local equivalence preserves qualitative conclusions and comparative statics.

the approach and the estimated parameters.

2.4 Trade Shocks and Equity Risk Premia

To characterize equity risk premia in the presence of trade shocks, it is useful to define the log of the SDF, or log pricing kernel $m_{i,2}$ at time $t = 2$. This paper explores two proxies for the stochastic discount factor (SDF): the global market factor from the world capital asset pricing model (CAPM), and global consumption growth from the world consumption capital asset pricing model (CCAPM). Section C.5 in Appendix C derives both proxies within this paper's model. If the log pricing kernel and the log excess stock return $rx_{ki,2}$ are jointly normal, then the standard Euler equation $E_t\left[M_{t+1}R_{ki,t+1}\right] = 1$ implies that the expected excess equity return in levels is the conditional covariance between m_{t+1} and $rx_{i,t+1}$.

[8] $$E_{t=1}\left[rx_{ki,2}\right] + \frac{1}{2}Var_{t=1}\left(rx_{ki,2}\right) = -Cov_{t=1}\left(m_2, rx_{ki,2}\right)$$

In the presence of supply-side cost shocks, the nonlinearity of the shocks rules out an analytical formula for [8]. Therefore, I use a simulation approach in Section 2.4.2 to characterize expected excess equity returns under the full model with simultaneous supply-side and demand-side shocks. However, to aid in the interpretation of these results, I first derive an analytical expression in Section 2.4.1 for $-Cov_{t=1}\left(M_{t+1}, R_{ki,t+1}\right)$ in the absence of supply-side cost shocks. Although this expression does not characterize the full model with nonlinear supply-side interactions, it offers partial intuition for the simulated results by isolating the effects of demand-side shocks.

2.4.1. *Demand-Side Trade Shocks and Equity Risk Premia*

When demand-side trade shocks follow the distribution assumptions described in Section 2.2, a formula can be derived for $-Cov_{t=1}\left(M_{t+1}, R_{ki,t+1}\right)$. I begin by expressing equity returns in terms of demand-side trade shocks under the assumption that costs do not change from time $t = 1$ to time $t = 2$ (i.e., no supply-side shocks).

[9] $$\mathrm{R}_{ki,2} = \delta \frac{\Pi_{ki,1}}{2\sum_{n\in\Lambda_{ki,1}} x_{kn,1}}$$

$$-\delta \frac{\kappa_d \sum_{n\in\Lambda_{ki,1}} x_{kn,1}\left(\zeta_{k,n,2}+\varepsilon_{n,2}+\eta_{g,2}+\nu_{j,g,2}\right)}{2\sum_{n\in\Lambda_{ki,1}} x_{kn,1}} - \frac{\kappa_d \sum_{n\in\Lambda_{ki,1}} x_{kn,1}\left(\zeta_{k,n,2}+\varepsilon_{n,2}+\eta_{g,2}+\nu_{j,g,2}\right)}{\Pi_{ki,1}}$$

[10] $$\mathrm{R}_{ki,2} = \delta \frac{\Pi_{ki,1}}{2\sum_{n\in\Lambda_{ki,1}} x_{kn,1}}$$

$$-\kappa_d\left(\zeta_{k,n,2} + \eta_{g,2} + \nu_{j,g,2} + \sum_{n\in\Lambda_{ki,1}} \iota_{kn,1}\varepsilon_{n,2}\right)\left[\frac{\delta}{2} + \frac{\sum_{n\in\Lambda_{ki,1}} x_{kn,1}}{\Pi_{ki,1}}\right], \text{ where}$$

$$\iota_{kn,1} = \frac{x_{kn,1}}{\sum_{n\in\Lambda_{ki,1}} x_{kn,1}} \text{ and } pm_{ki,1} = \frac{\Pi_{ki,1}}{\sum_{n\in\Lambda_{ki,1}} x_{kn,1}}$$

In [10], $\iota_{kn,1}$ is the weight of the revenue earned by firm k in economy n as a percentage of the total revenue earned by firm k, while $pm_{ki,1}$ is the profit margin for firm k.

As for the CCAPM SDF (see Section C.5 in Appendix C), when firm-level shocks and economy-level shocks "average out," global consumption growth can be reduced to a simple function of the homogenous global shock under the assumption of no supply-side shocks.

[11] $$-M_2 = \frac{C^*_{G,2}}{C^*_{G,1}} = 1 - \kappa_d\left(1+\rho_{\eta\nu}\right)\eta_{g,2}$$

Together, [10] and [11] engender the following representation for expected excess equity returns.

[12] $$-Cov_{t=1}\left(M_{t+1}, R_{ki,t+1}\right) = \left(\frac{\delta}{2} + \frac{1}{pm_{ki,1}}\right)\left[\kappa_d^2\left(1+\rho_{\eta\nu}\right)^2\right]$$

Equation [12] presents a familiar structure for the equity risk premium. It is the product of the quantity of equity risk β_{ki} for firm k, and the world equity price of risk λ^g.

[13] $$\beta_{ki} = \left(\frac{\delta}{2} + \frac{1}{pm_{ki,1}}\right)$$

[14] $$\lambda^g = \kappa_d^2\left(1+\rho_{\eta\nu}\right)^2$$

Equation [13] shows that β_{ki} is a function of the dividend-profit ratio δ, the equity-to-sales ratio, and the profit margin for firm k. In the model, there is a common dividend-profit ratio δ, and 2 is

the common equity-to-sales ratio. Crucially, β_{ki} varies inversely with the profit margin for firm k at time $t = 1$.

When costs do not change from time $t = 1$ to time $t = 2$, the expected excess equity return is linear in β_{ki}. Dominant firms that exhibit a greater margin of competition are less risky compared to vulnerable firms with a small margin of competition. However when costs are allowed to change, expected excess equity returns may exhibit nonlinearities. Importantly, supply-side displacement risk does not merely strengthen the demand-side relation between profitability and risk premia, but qualitatively alters its shape near zero profitability.

2.4.2. *Supply-Side Trade Shocks, Single-Factor Contamination and Equity Risk Premia*

In the presence of supply-side cost shocks, nonlinearities prevent a closed-form solution for the expected excess equity return. In lieu of a closed-form solution, an examination of the distribution of possible outcomes offers insights into the ways that equity risk premia are impacted by imperfect global competition. The economic mechanisms underlying these nonlinear effects are illustrated in a stylized toy example in Section B.1 (see Appendix B), which isolates competitive displacement on the supply side and clarifies its implications for asset pricing. The nonlinearities reflect asymmetric responses to competitive displacement across firms, with return volatility and tail risk concentrated among vulnerable firms.

The interaction between dominant and vulnerable firms suggests that single-factor proxies of the SDF may be contaminated due to imperfect competition. At the root of this contamination is the fact that the single-factor SDF proxy (e.g., global consumption growth) is not merely an exogenous source of systematic risk, but is largely shaped by the ex-post performance of dominant firms. Vulnerable firms, in comparison, contribute very little to the SDF proxy and may exhibit a weak SDF exposure despite the severe displacement risk (see Sections B.1.4 and B.1.5).

Competitive displacement also introduces a direct contrarian mechanism in general equilibrium that compounds this weighting effect: Dominant firms capture additional product markets precisely when vulnerable firms lose markets. The result is that vulnerable firms exhibit contrarian SDF exposures because the proxy reflects the competitive gains of dominant firms, which in turn exhibit conventional but exaggerated exposures. These dominant firms may appear highly exposed to systematic risk when in fact their positions are buffered by dominance in product markets.

To determine whether global imperfect competition engenders these nonlinear contrarian outcomes under the full model with simultaneous demand-side and supply-side shocks, I use the simulation algorithm along with the identified return generation parameters from Section C.4 in Appendix C to conduct five simulation trials. Across all five trials, there is a total of 6,774 simulated operating firms at time $t = 1$, and a total of 677,400 data points (i.e., 6,774 simulated operating firms with 100 profiles for each firm). Using the generated values of global consumption growth (see Section C.5.2), I produce the log of the SDF m_2. I also produce the log of the excess equity return $rx_{ki,2}$, and the expected excess equity returns in [8].

In Figure 1, the left side of Panel A shows the relation between expected excess equity returns and the SDF covariance $Cov_{t=1}(m_2, rx_{ki,2})$. The first contrarian finding is that there are numerous instances where the simulated SDF covariance is positive. Positive covariances do not align well with the CCAPM theory that links negative covariances to positive equity risk premia. The second contrarian finding is that the relation is mostly nonlinear. The R^2 for the quadratic fit is roughly 0.299, while the R^2 for the linear fit is approximately 0.021. The third contrarian finding is that the linear coefficient is positive, which is inconsistent with the negative linear relation predicted by the CCAPM theory.

Following the construction of the value-weighted market return in Section C.5.1, I also

produce the global market factor from the simulation outcomes. I then regress simulated excess equity returns on the global market factor to produce global market betas. The right side of Panel A shows the relation between expected excess equity returns and the global market betas. Consistent with the results for the SDF covariance, the figure shows similar contrarian findings: negative global market betas, a nonlinear relation between expected excess equity returns and global market betas, and a negative linear coefficient for the relation (i.e., inconsistent with the theory of the CAPM).

Although inconsistent with CAPM and CCAPM, the findings in Panel A of Figure 1 are consistent with the expected interaction between dominant firms and vulnerable firms in a globally competitive marketplace. If dominant firms are disproportionately represented in global consumption growth and the global market factor, then vulnerable firms will exhibit contrarian SDF exposures.

These contrarian exposures reflect a nonlinear mapping between SDF exposure and expected excess equity returns that arises from competitive displacement rather than from the conventional linear risk–return tradeoff. Although their measured exposure to the SDF proxy is weak or contrarian, vulnerable firms exhibit large expected excess returns because of displacement risk and its severe downside potential. Dominant firms, by contrast, exhibit strong and conventional SDF exposures because they disproportionately shape aggregate outcomes, yet their dominant product market shares buffer them from comparable displacement risk. Consequently, expected excess returns are high at both ends of the SDF-exposure distribution, driven by displacement risk for vulnerable firms and by aggregate exposure for dominant firms. Firms in intermediate competitive positions are not greatly influenced by either force.[19] This asymmetry

[19] In Appendix B, Section B.1.5 shows that this nonlinear pattern emerges when demand-side shocks receive a much greater weight than supply-side shocks. In the toy example, demand-dominated fluctuations are necessary to match

generates a nonlinear, and potentially U-shaped, relation between expected excess equity returns and SDF exposures, with a contrarian linear coefficient when approximated by a single-factor regression (positive for global consumption growth, and negative for the global market factor).

Panel B of Figure 1 shows that imperfect competition not only engenders contrarian SDF exposures. Imperfect competition may also engender noise in the estimation of global market betas (and a corresponding lack of statistical significance). In Panel B, I distinguish between statistically significant global market betas and statistically insignificant global market betas, while showing the regression fit for significant betas only. In comparison to the corresponding figures in Panel A, the regression coefficients exhibit the correct signs when applying a linear fit to significant betas. Consistent with the idea of single-factor SDF proxy contamination, the finding suggests that the contrarian linear coefficients occur mainly for noisy SDF exposures.

Does imperfect global competition play a central role in contrarian outcomes? In Figure 2, I focus on local SDFs to test whether the findings in Figure 1 are driven by imperfect competition. In the model, firms do not compete locally. Therefore, by relating expected excess equity returns to the local SDF covariance, I can observe what would occur in the absence of competition. The findings are striking. Compared to the corresponding figures in Panel A of Figure 1, there is much less evidence of contrarian outcomes. First, there are very few instances of contrarian SDF exposures. Second, the relation between expected excess equity returns and the SDF exposure is mostly linear. Finally, the coefficient signs are consistent with standard international asset pricing theories.

Panel C of Figure 2 explores the role of dominant firms in contrarian outcomes. Here I

realistic aggregate return volatility, yet even at relatively small weights, supply-side displacement risk materially affects the cross section, producing high risk premia for vulnerable firms. This mirrors the SMM results in Section C.4 (Appendix C), where matching the moments of global stock returns implies a large relative weight on demand-side shocks.

produce an *equal-weighted* global market return from the simulation outcomes. Compared to its value-weighted counterpart, the equal-weighted global market return is less influenced by dominant firms. I then regress simulated excess equity returns on an equal-weighted excess global market factor to produce equal-weight global betas. Compared to the corresponding figures in Panel A of Figure 1, the linear coefficients exhibit the correct signs. This finding suggests that the contrarian linear coefficient reflects contamination from dominant firms in the value-weighted market factor; reducing their influence through equal-weighting yields conventional coefficient signs.

Taken together, the results in Figures 1 and 2 offer compelling evidence that in the presence of simultaneous demand-side and supply-side shocks, imperfect global competition can give rise to the contamination of single-factor SDF proxies, contrarian SDF exposures, and a contrarian linear coefficient for the relation between expected excess equity returns and SDF exposures.

2.4.3. *Contrarian SDF Exposure and the Identification of Multiple Factors*

The contamination of traditional single-factor SDF proxies under competitive displacement raises the question of how to correct for this contamination in a setting with simultaneous demand-side and supply-side shocks. While an analytical solution would ideally characterize the correct SDF that accounts for competitive displacement, the nonlinearities introduced by supply-side cost shocks prevent such a solution. Instead, I use the model itself as a laboratory to identify which firm-level and economy-level characteristics are associated with contamination. Specifically, I implement a logit regression on simulated firms to isolate the characteristics related to contrarian or noisy SDF exposures (i.e., the signatures of factor contamination). These characteristics then inform the construction of candidate factors for a linear multifactor pricing model that corrects for contamination.

Table 2 presents the results of a logit model that relates firm-level and economy-level model characteristics to binary indicators for contrarian SDF exposures and noisy SDF exposures. Column (7) presents the results of a logit regression where simulated firms from the home economy are excluded. The economy-level model regressors are the input cost in economy i at time $t = 1$, $c_{i,1}$, the log of the total income in economy i at time $t = 1$, $\ln(Y_{i,1})$, the log of the state of technology (a measure of absolute advantage) in economy i, $\ln(T_i)$, and the log of the average import openness in economy n, $\ln(d_n)$. The firm-level model regressors are the log of total revenue of firm k from economy i at time $t = 1$ multiplied by 2, $\ln(2\sum_{n\in\Lambda_{ki,1}} x_{kn,1})$, and the profit margin of firm k from economy i at time $t = 1$, $pm_{ki,1}$. These economy-level and firm-level regressors are standardized. I also sort source economies based on excess currency returns (in terms of the currency of the home economy), and include indicator variables for whether economy i at time $t = 1$ belongs to a portfolio quintile.[20]

In Table 2, I report the marginal effects for the firm-level regressors. Consistent with [12] and the importance of the interaction between dominant firms and vulnerable firms, a firm's competitive profit margin is the most important determinant of whether its SDF exposure is conventional or precise. The marginal effect for $pm_{ki,1}$ is roughly −0.404 and is statistically significant at the 1% level.[21] The finding suggests that vulnerable firms with thin profit margins are more likely to exhibit contrarian or noisy SDF exposures. Firm size is also important. The marginal effect for $\ln(2\sum_{n\in\Lambda_{ki,1}} x_{kn,1})$ is approximately −0.040 and is statistically significant at

[20] The log of the SDF, or log pricing kernel in economy i, $m_{i,2}$, is the log of consumption growth at time $t = 2$. In an environment with complete markets, the change in the real exchange rate $\Delta q_{i,2}$ between a home economy (e.g., United States) and economy i at time $t = 2$ is $\Delta q_{i,2} = m_{h,2} - m_{i,2}$. By defining (in logarithms) the real risk-free interest rate $r_{i,t}$ for economy i at time t as $-E_t[m_{i,t+1}] + \frac{1}{2}Var_t(m_{i,t+1})$, the log of excess currency returns for economy i at time $t = 2$ can be defined as $crx_{i,2} = r_{i,1} - r_{h,1} - \Delta q_{i,2}$.

[21] In Appendix B, Table B.1 investigates a specification with industry concentration (Hou and Robinson, 2006) in place of $pm_{ki,1}$, and finds a consistent marginal effect of 0.029 that is statistically significant at the 1% level.

the 1% level. The finding suggests that small firms that don't produce for many destination markets are more likely to exhibit contrarian or noisy SDF exposures.

Economy-level characteristics are also related to whether a firm exhibits contrarian or noisy SDF exposures. Consistent with the importance of imperfect global competition, firms in economies with greater import barriers are less likely to exhibit contrarian or noisy SDF exposures. The marginal effect for $\ln(d_n)$ is roughly -0.026 and is statistically significant at the 1% level. Firms from economies with a higher state of technology are also less likely to exhibit contrarian or noisy SDF exposures. The marginal effect for $\ln(T_i)$ is roughly -0.013 and is statistically significant at the 5% level. Finally, currency risk premia seems to be important. Compared to firms from economies in the lowest CRX portfolio (Q1), firms from economies in the highest CRX portfolio (Q5) are less likely to exhibit contrarian or noisy SDF exposures. The marginal effect of the Q5 CRX portfolio indicator is approximately -0.099 and statistically significant at the 1% level.

The findings in Table 2 suggest that firm size and profitability could be used to create important risk factors for estimating global equity risk premia. Figure 4 explores whether these firm-level characteristics are also associated with expected excess equity returns when SDF exposures are contrarian or noisy. The left side of Panel A shows the results for firm size when distinguishing between conventional SDF exposures and contrarian SDF exposures. I find that there is a negative relation between firm size and expected excess equity returns precisely when SDF exposures are contrarian. The right side of Panel A shows similar results when distinguishing between precise SDF exposures and noisy SDF exposures with a negative relation between firm size and expected excess equity returns when SDF exposures are noisy.

The left side of Panel B examines firms with contrarian SDF exposures and reveals a

nonlinear relation between relative profitability and expected excess equity returns. When firms exhibit conventional SDF exposures, profitability is only weakly related to equity risk premia. By contrast, among firms with contrarian SDF exposures, expected excess equity returns rise sharply as relative profit margins decline. This relation is highly nonlinear: as profits approach zero, expected returns increase much more steeply than the inverse relation implied by demand-side mechanisms alone.[22] The right side of Panel B demonstrates a similar pattern for firms with noisy SDF exposures.

3. Data and Sample Statistics

For a sample of stocks in multiple economies, this paper examines how international trade and imperfect competition shape global equity risk premia. The data for currencies, common stocks, and company accounts are initially extracted from the Datastream and Worldscope databases for the period of January 1975 to March 2025. Given the role of currency returns in the multifactor framework, I use an initial sample of 55 currencies as the basis for constructing a sample of economies. Common stocks are selected from the major exchange(s) in each sample economy. For most economies, the exchange with the largest number of traded stocks is chosen. The exceptions are China (Shanghai and Shenzhen), Japan (Osaka and Tokyo), and the United States (AMEX, Nasdaq, and NYSE). After screening for non-missing economy-level data, the final sample consists of 64740 stocks from 55 economies for the months July 1989 to June 2024. The variable definitions are presented in Table 3, while the economy-level summary statistics, variable descriptions, and data sources are presented in Appendix A.

[22] In a setting limited to demand-side shocks (Section 2.4.1), expected excess equity returns scale approximately with the inverse of the relative profit margin (see equation [12]), exhibiting a smooth inverse relation. In the presence of supply-side displacement risk, however, the simulated relation steepens markedly as profits approach zero, exhibiting extreme nonlinearity near displacement as predicted by the theory. This suggests that supply-side competition amplifies the demand-side mechanism by introducing severe downside risk when relative profit margins are low.

3.1 Excess Stock Returns

In constructing monthly stock returns for analysis, I implement standard data screens. To minimize biases from low-priced stocks, a minimum price of one dollar in the prior month is required for a valid monthly return. In addition, each return above 300% that is reversed within one month is set to a missing value.[23] To address any remaining anomalies in returns that cannot be identified by corporate price events (i.e., stock splits, mergers, etc.), I set the monthly return to a missing value if it is outside of the 0.025th and 99.975th percentiles for each economy. When a firm delists, its return series ends at the last observed return; no backfilling or post-delisting return imputation is applied. *Excess return* is the monthly return (in US dollars) to buying the stock at time $t - 1$ and then selling it at time t, in excess of the risk-free rate (taken from Kenneth French's Data Library).

3.2 Portfolios Based on Firm Characteristics

The firm-level characteristics used for portfolio construction are *Market value of equity* and *Industry-adjusted return on equity*. These two variables are meant to capture $2\sum_{n\in\Lambda_{ki,1}} x_{kn,1}$ and $pm_{ki,1}$ in this paper's model while aligning with the conventional empirical asset pricing literature. *Market value of equity* is the total market capitalization of a firm's equity in millions of United States (US) dollars (Datastream/Worldscope data item: Market Value). Raw (current) values are converted to real June 2024 values using the US Consumer Price Index (CPI). *Industry-adjusted return on equity* is the residual (in percentage points) from a regression of return on equity (Datastream/Worldscope data item: WC08301) on industry fixed effects (two-digit standard industry classification, SIC, code) for all firms using the full data extraction period (January 1975 to March 2025). The full data extraction period is used to compute the most precise estimates of average profitability at the industry level.

[23] If r_t or r_{t-1} is greater than 300%, and $(1 + r_t)(1 + r_{t-1}) - 1 < 0.5$, then both r_t and r_{t-1} are set to missing values.

Following Fama and French (1992), this paper uses both single-sorting and double-sorting procedures for portfolio construction. In the single-sorting procedure, five portfolios are constructed on the basis of global quintile sorts of the sorting variable. The stocks with the smallest values of the sorting variable are assigned to Quintile 1 (Q1), whereas stocks with the largest values are assigned to Quintile 5 (Q5). In the double-sorting procedure, two portfolios are constructed on the basis of the global median cutoff for the first sorting variable, and within each of these portfolios, five portfolios are constructed on the basis of global quintile sorts of the second sorting variable. In both procedures, portfolios are formed at the end of June of year y for evaluation of monthly returns from July of year y to June of year $y + 1$. In the case of SIZE portfolios, the sorting variable is *Market value of equity* in June of year y. In the case of the IAROE portfolios, the sorting variable is *Industry-adjusted return on equity* in December of year $y - 1$.

3.3 Portfolios Based on Economy Characteristics

The economy-level characteristics used for portfolio construction are *Technology* and *Trade protection*. These two variables are meant to proxy for absolute advantage and trade barriers in this paper's model. *Technology* is the (current) gross domestic product (in US dollars), while *Trade protection* is the (interpolated) weighted average of the import tariff rate across all products in an economy. For these economy-level characteristics, this paper uses a single-sorting procedure for portfolio construction, where five *stock* portfolios are constructed on the basis of global quintile sorts of the economy-level sorting variable. The stocks with the smallest values of the sorting variable are assigned to Q1, whereas stocks with the largest values are assigned to Q5. In this procedure, portfolios are formed at the end of June of year y for evaluation of monthly returns from July of year y to June of year $y + 1$. In the case of TECH portfolios, the sorting variable is

Technology in year $y - 1$. In the case of TDPRT portfolios, the sorting variable is *Trade protection* in year $y - 1$.

3.4 Portfolios Based on Industry Profitability Dispersion

High profitability dispersion within industries occurs with active competitive displacement. To test whether the intensity of competitive displacement is priced, I construct portfolios sorted on *Industry profitability dispersion*, or the interquartile range for return on equity within an industry. For this industry-level characteristic, this paper uses a single-sorting procedure for portfolio construction similar to that for the economy-level characteristics in Section 3.2 (i.e., stocks with the smallest values are assigned to Q1, while stocks with the largest values are assigned to Q5). In this procedure, five *stock* portfolios are formed at the end of June of year y for evaluation of monthly returns from July of year y to June of year $y + 1$. In the case of these IDISP portfolios, the sorting variable is *Industry profitability dispersion* in December of year $y - 1$.

3.5 Currency Return Portfolios

Mean currency excess return serves as the basis for creating excess currency return portfolios. The variable is defined as the annual average of the excess currency return in an economy, where the excess currency return is computed as the monthly return (in US dollars) to buying a foreign currency in the forward market (at the forward rate) at time $t - 1$ and then selling it in the spot market (at the spot rate) at time t. Using a single-sorting procedure for portfolio construction, I create five *currency* portfolios on the basis of global quintile sorts of *Mean currency excess return* in year $y - 1$. The currencies with the smallest values of the sorting variable are assigned to Q1, whereas currencies with the largest values are assigned to Q5.

This construction is motivated by the simulation results in Table 2. Simulated firms in economies with the lowest excess currency returns tend to exhibit negative or insignificant global

market betas relative to firms in economies with the highest excess currency returns, particularly after controlling for economy-level characteristics. The simulation result suggests that excess currency returns play an important role in a multifactor framework. Moreover, currency risk may be priced for international stocks (Lewis, 2011; Brusa, Ramadorai, and Verdelhan, 2015; Karolyi and Wu, 2021).

3.6 Global Factors

Informed by the theoretical findings in this paper, I study five global factors (i.e., global sorts) in addition to the global market factor: the size factor (SIZE), the profit vulnerability factor (IAROE), the technology factor (TECH), the trade protection factor (TDPRT), and the currency factor (CRX). *Global market factor* (GMKT) is the monthly return (in US dollars) of the global Morgan Stanley Capital International (MSCI) index in excess of the risk-free rate.

The remaining global factors are constructed as long-short factor-mimicking portfolios. Ten double-sorted portfolios (P1 to P10) are used to construct the SIZE and IAROE factors as long-short portfolio return averages. P1 to P5 represent the five IAROE portfolios within the below-median size group, while P6 to P10 represent the five IAROE portfolios within the above-median size group. The SIZE factor is the average return of P1 to P5 (SIZE1) minus the average return of P6 to P10 (SIZE2). Typically asset pricing factors are constructed using the two extremes of a portfolio distribution (e.g., Q1 and Q5). However, the IAROE factor is the average return of P1 and P6 (IAROE1) minus the average return of P2 and P7 (IAROE2) because displacement risk concentrates at the vulnerable tail where extreme nonlinearity emerges. The TECH, TDPRT, and CRX factors are constructed as Q5 – Q1 long-short factor-mimicking portfolios.

4. Empirical Analysis of Global Stock Returns

This section evaluates the empirical relevance of competitive displacement and factor

contamination for global equity risk premia. Appendix B presents various robustness checks of the main empirical findings. The model predicts that single-factor proxies for the stochastic discount factor become unreliable when competitive displacement is most active, with effects strongest for small firms and firms with low profitability relative to competitors, and intensifying during periods of elevated displacement risk

The empirical analysis has three components. First, I construct portfolios sorted on firm-level characteristics that proxy for vulnerability to displacement (firm size and industry-adjusted return on equity) as well as economy-level characteristics that govern the transmission of competitive shocks. Second, I estimate factor loadings and risk premia for both the world CAPM and this paper's multifactor model using a conditional generalized method of moments (GMM) approach, allowing for a comparison of pricing performance. Third, I evaluate whether explicitly modeling displacement risk explains why single-factor models fail, both unconditionally and during periods of severe competitive displacement.

This paper's model motivates two central questions for empirical analysis. First, do firms that are most vulnerable to competitive displacement earn systematically higher excess returns despite weak or unstable market exposures? Second, does the modeling of displacement risk correct the pricing failures of single-factor models? Addressing these questions reveals both whether the multifactor model improves upon existing benchmarks and why—by correcting for factor contamination.

4.1 Portfolio Summary Statistics

Table 3 presents the summary statistics of international equity portfolios sorted on various firm-level and industry-level measures.

4.1.1. *Portfolios Based on Firm Characteristics*

Panel A of Table 3 reports the summary statistics for the portfolios double sorted, first on *Market value of equity*, and then on *Industry-adjusted return on equity*. Portfolios P1 to P5 contain relatively small firms, while P6 to P10 contain larger firms. Within each size group, lower portfolio numbers correspond to weaker profitability relative to industry competitors. The mean industry-adjusted return on equity (ROE) for P1 is roughly −5141%. In comparison, the least profitable large firms in P6 do not exhibit nearly the same level of profit vulnerability relative to global competitors, underscoring the asymmetric role of firm size in buffering competitive shocks.

This paper's model predicts that equity risk premia increase sharply as relative profitability approaches zero (Panel B of Figure 3). Consistent with this prediction, the findings presented in Panel A of Table 3, and in Figure B.2 in Appendix B reveal that IAROE1 (the average of P1 and P6) earns a monthly value-weighted average excess return of 2.42%, substantially exceeding 1.61% for IAROE2. The difference of roughly 0.80% is statistically significant at the 1% level. In addition, the portfolio with the greatest relative profitability (IAROE5) earns a significantly larger mean excess return compared to IAROE2.

Taken together, these findings reject the null hypothesis of no relation between a firm's excess equity returns and its *Industry-adjusted return on equity*. Instead, the findings support the model's central implication that competitive displacement generates a highly nonlinear relation between relative profitability and excess returns, with firms closest to displacement commanding a large risk premium.

4.1.2. *Portfolios Based on Industry Profitability Dispersion*

Panel B of Table 3 reports summary statistics for portfolios sorted on *Industry profitability dispersion*, which proxies for the intensity of competitive displacement. Average monthly excess

returns increase from roughly 0.64% in the lowest-dispersion quintile (Q1) to roughly 1.12% in the highest-dispersion quintile (Q5). The findings in Panel B motivate an empirical test of whether a single global market factor can explain the return spread.

4.2 Factor Summary Statistics and Correlations

In Table 3, Panel C shows the summary statistics for all global factors. The mean for the GMKT factor is roughly 0.55% (6.7% annualized) with an annualized Sharpe ratio of roughly 0.41. The SIZE factor exhibits the largest mean of all the factors at approximately 1.76% (21.07% annualized), consistent with the concentration of displacement risk among small firms. The IAROE factor captures profit vulnerability by comparing the most vulnerable portfolios (IAROE1) to the next quintile (IAROE2), reflecting the sharp risk premium increase as relative profitability approaches zero. This IAROE factor exhibits a mean of roughly 0.80% (9.65% annualized) with a Sharpe ratio of approximately 1.12. The CRX exhibits a mean of nearly 0.93% (11.14% annualized) with noticeable serial correlation relative to other factors. The TECH and TDPRT factors exhibit modest monthly means (−0.46% and 0.23%, respectively) but substantial higher-order moments, reflecting their potential as state variables rather than standalone sources of priced risk. Panel D shows the global factor correlations. IAROE is modestly correlated with the GMKT and SIZE factors, and the TDPRT factor is modestly correlated with the SIZE and TECH factors.

4.3 Time-Series Regressions: Size and Industry Profitability Dispersion Anomalies

If a contaminated market factor cannot correctly distinguish between small vulnerable firms and large dominant firms, then a global long-short portfolio based on firm size (small minus big) should earn a significant CAPM alpha. Likewise, if a contaminated market factor cannot distinguish dominant winners from vulnerable losers within industries, then a global long-short portfolio based on industry profitability dispersion (high minus low dispersion) should also earn a significant

CAPM alpha. This subsection examines whether the six global factors (GMKT, SIZE, IAROE, TECH, TDPRT, and CRX) reduce these alphas in simple time-series regressions.

Panel A of Table 4 reports regression results for the world CAPM. The global small-minus-big portfolio yields a market beta of approximately −0.21, consistent with the prediction that small firms exhibit weaker exposures to the contaminated factor compared to large firms. The corresponding CAPM alpha is nearly 1.86% per month and is statistically significant at the 1% level. The global high-minus-low industry profitability dispersion portfolio also earns a significant CAPM alpha of roughly 0.45% per month that is statistically significant at the 1% level.

Panel B reports regression results when the six global factors are included.[24] For the global small-minus-big portfolio, both the alpha and the absolute value of the market beta decline substantially. While the market beta becomes approximately −0.16, the monthly alpha falls to roughly 50 basis points, but remains statistically significant at the 1% level. For the global high-minus-low industry profitability dispersion portfolio, the monthly alpha drops to roughly −0.07% and is no longer statistically significant at the 10% level or less.[25] These results suggest that an explicit modeling of competitive displacement attenuates the systematic mis-pricings that emerge with contaminated single-factor models.[26]

4.4 Multifactor Model Design

This section outlines the construction of the paper's multifactor asset-pricing model, which is designed to correct for factor contamination arising from competitive displacement in global

[24] Table B.3 in Appendix B shows the coefficient results for all six global factors.

[25] This global six factor specification is unique in reducing the alpha for the global long-short industry profitability dispersion portfolio. Table B.8 in Appendix B shows that the five world Fama-French factors do not materially explain the size and industry profitability dispersion anomalies.

[26] Both the global small-minus-big portfolio and the global high-minus-low industry profitability dispersion portfolio exhibit statistically significant exposure to the IAROE factor, indicating that their excess returns are systematically related to profit vulnerability. This result shows that the size and dispersion anomalies reflect common exposure to competitive displacement operating through relative profitability, rather than unrelated sources of risk.

product markets. The multifactor model design proceeds in two steps. First, I use the logit analysis in Table 2 to identify characteristics associated with contrarian or noisy SDF exposures. Second, I evaluate each characteristic's economic role to classify it as a priced factor or a conditioning variable.

Table 2 shows that firm size, relative profitability, technology, trade protection, and excess currency returns could be linked to factor contamination. I evaluate whether each characteristic's factor-mimicking portfolio can proxy for systematic risks or whether it determines the state of competitive displacement.

Systematic risks are those that investors cannot avoid through diversification. Competitive displacement risk satisfies this definition: as an economic force pervading global product markets, investors cannot simultaneously avoid exposure to dominant and vulnerable firms. The multifactor model recognizes firm size and relative profitability as firm-level characteristics that capture different dimensions of vulnerability: market scale and competitive position. Panel A of Table 3 shows that both characteristics command significant risk premia. Hence SIZE and IAROE qualify as priced factors. CRX also qualifies as a priced factor based on a large body of research linking currency risk premia to global risk exposure (Lustig, Roussanov, and Verdelhan, 2011; Menkhoff et al., 2012).

Conditioning variables primarily govern how displacement risk transmits across economies. Although Table 2 identifies technology and trade protection as significant predictors of contrarian or noisy SDF exposures, these economy-level characteristics typically suffer from econometric problems when treated as priced factors (Kan and Zhang, 1999; Gospodinov, Kan, and Robotti, 2014). They function more effectively as factor-mimicking portfolios capturing time-

varying states of competitive displacement. Hence TECH and TDPRT qualify as conditioning variables.

4.4.1. *Conditioning Instrumental Variables, Structural Breaks, and Displacement Periods*

This paper's conditional GMM estimation uses principal components derived from the technology (TECH) and trade protection (TDPRT) factors as conditioning instrumental variables. These instruments capture time-varying competitive states that govern how displacement risk transmits across economies.

To generate these principal components, I construct seven functional forms from TECH and TDPRT: current values, first and second lags, squared terms, and their interaction. Principal component analysis then extracts three orthogonal instruments from these variables. The first principal component loads primarily on interaction and dynamic terms, while the second and third components are largely associated with variation in technology and trade protection, respectively. Together, these components maintain orthogonality while capturing the time-varying nature of competitive conditions.

To identify periods of severe competitive disruption (i.e., displacement periods), I use structural break tests on the principal components along with TECH and TDPRT. The Bai-Perron test (Bai and Perron, 1998) identifies structural breaks in each series, with breaks occurring within 10 months clustered into discrete episodes. The procedure does not use pricing errors or model fit in break detection. This procedure identifies six major displacement episodes between July 1989 and June 2024. Figure 4 presents the twelve-month moving averages of the three principal components over time, with displacement periods highlighted.[27]

[27] Figure 4 shows the major episodes as shaded regions: the Mexican peso crisis (MPS), the Asian financial crisis (AFC), the dot-com bust (DCB), the great trade collapse following the global financial crisis (GFC), the taper tantrum (TTM), and the US-China trade war (TRD). These episodes correspond to well-documented periods of severe disruption. Months not falling within these episodes are classified as "normal periods." The classification of

4.5 Time-Series Regressions: State-Dependent Evidence of Factor Contamination

The factor contamination framework predicts that traditional single-factor models exhibit systematic misspecification during displacement periods, not because of a time-varying market beta, but because an endogenous market proxy conflates displacement risk with global economic risk. In Table 5, I examine how factor exposures differ across normal and displacement periods to test whether single-factor regressions display state-dependent misspecification, and whether this misspecification reflects factor contamination

Under the world CAPM, the market beta is constant, so if the world CAPM is correctly specified, then the estimated market beta should remain stable across economic states. If the world CAPM is misspecified, then market beta may become unstable during displacement periods. Specifically, the factor contamination framework predicts that the beta instability should disappear once displacement risk is explicitly modeled, with a reassignment of exposure to displacement factors during displacement periods.

Table 5 reports time-series regressions for the global high-minus-low industry profitability dispersion portfolio. I estimate exposures separately for normal periods and displacement periods, with statistical significance of differences determined through a single regression including displacement interaction terms. Columns (1) and (2) present results for the single market factor. During normal periods, the market beta is nearly 0.01 and not statistically significant at the 10% level or less. During displacement periods, the beta becomes roughly 0.20, representing a difference of 0.19 that is statistically significant at the 1% level. These findings suggest that the

displacement and normal periods allows for a comparison of model performance across competitive states, testing whether the multifactor model maintains pricing accuracy when factor contamination is predicted to be most severe. Figure B.5 in Appendix B presents an alternative view using twelve-month moving averages of the original TECH and TDPRT factors rather than the principal components, allowing for a more transparent economic interpretation.

conventional exposure for this portfolio is largely driven by episodes of severe competitive displacement. Moreover, the beta instability indicates that the single-factor model is misspecified.

Columns (3) and (4) of Table 5 present results when all six factors are included, reporting exposures for the market factor and IAROE factor. For the market factor, the market beta during normal periods is roughly −0.06, shifting to roughly 0.01 during displacement periods. The difference of 0.07 is not statistically significant at the 10% level or less. This beta *stability* contrasts sharply with the single-factor case, indicating that an explicit modeling of displacement risk eliminates beta instability.

For the IAROE factor, the exposure during normal periods is nearly 0.46, increasing to roughly 0.86 during displacement periods. This shift confirms that displacement risk operates through the competitive vulnerability dimension captured by IAROE. The pattern of a stable market beta and a shifting IAROE exposure is consistent with contamination rather than generic state-invariant omitted variables. Once the six factors are included, the beta instability disappears and the exposure is reassigned to the theoretically predicted location: the IAROE factor. In Table 5, column (5) imposes the theoretical restriction of a fixed market beta (no state-dependent instability), where the market factor is correctly specified once displacement risk is modeled. Imposing this maintained restriction increases precision: the change in the exposure to the IAROE factor is nearly 0.50, and is statistically significant at the 5% level (compared to 0.40 unrestricted with a p-value of 0.14).

Taken together, the results in Table 5 provide evidence of factor contamination arising from state-dependent misspecification induced by competitive displacement. In the single-factor specification, displacement risk spuriously loads on the market factor, generating unstable market

betas. The six-factor specification clarifies this mechanism: displacement risk is instead captured by the IAROE factor, and market betas stabilize.

These results establish that the displacement risk premium cannot be explained by a generic state-invariant omitted factor. However, a natural concern is that the results in Table 5 reflect a generic state-dependent omitted factor rather than factor contamination (i.e., a structured state-dependent omitted factor arising from competitive displacement). Appendix B addresses this concern through three robustness tests. First, displacement-related patterns vary systematically with portfolios' exposure to competitive reallocation. Second, equal-weighting attenuates, but does not eliminate, these patterns. Third, value-weighting systematically amplifies displacement effects.[28]

4.6 Pricing Performance

The cross-sectional asset pricing tests investigate the pricing performance of this paper's multifactor model. In a linear factor model of asset pricing, excess returns can be represented as a function of risk factors; $RX_{it} = a_i + \boldsymbol{\beta}_i' \cdot \mathbf{f}_t + u_{it}$, where $i=1...N$ is an index for the test portfolios. In the absence of arbitrage, these excess returns are adjusted for risk using an SDF, M_t, thus satisfying the Euler equation, $E_t[M_{t+1}RX_{it+1}] = 0$. In [15], the SDF is represented as linear in the pricing factors where b is a vector of factor loadings and μ_{f} is a vector of factor means.

[15] $$M_{t+1} = 1 - b'(\mathbf{f}_{t+1} - \mu_{\mathrm{f}})$$

This linear representation is consistent with a beta pricing model where the expected excess return is equal to the factor price λ times the beta of each test portfolio, $E[RX_{it}] = \lambda'\beta_i$, with $\lambda = \Sigma_{\mathrm{f}} b$ and Σ_{f} being the variance-covariance matrix of the factors.

The factor prices λ and loadings b are estimated using both an unconditional generalized

[28] The results in Appendix B are also inconsistent with a general single-factor framework.

method of moments (GMM) approach (Hansen, 1982), based on unconditional moment restrictions with a constant instrument, and a conditional GMM approach specified through conditional moment restrictions. The conditional model employs three principal components extracted from TECH and TDPRT as lagged conditioning instruments. Standard errors use Newey-West (1987) with optimal lag selection.

The GMM approach requires the specification of a weighting matrix that determines the relative importance of the moment conditions (Hansen and Jagannathan, 1997; Hodrick and Zhang, 2001). This paper reports results based on both the Hansen–Jagannathan (HJ) weighting matrix (one-step estimation) and the optimal GMM weighting matrix (two-step estimation). When the HJ weighting matrix is used as the estimation criterion, the minimized objective function yields the Hansen–Jagannathan distance (UHJD), which measures the minimum pricing-error norm attainable within a given SDF specification.

For the unconditional model, parameter estimates are also obtained using the optimal GMM weighting matrix, given by the inverse of the long-run covariance matrix of the moments, which delivers asymptotically efficient estimates for each model. To facilitate a uniform comparison of pricing performance across models, the unconditional pricing errors implied by the optimally estimated SDF are additionally evaluated using the HJ metric (UHJM).[29] Similarly, for the conditional model, I compute a conditional HJ metric (CHJM) that evaluates pricing performance using conditioning information. Following the spirit of Gagliardini and Ronchetti (2020), CHJM measures pricing errors in a conditional payoff-space norm.[30]

[29] This HJ metric corresponds to the HJ inner product applied to the pricing-error vector at the optimal GMM estimates and is reported alongside the HJ distance to illustrate that both measures yield pricing-error magnitudes of comparable scale.

[30] Specifically, for the SDF estimated from optimal GMM, conditional pricing errors are evaluated period by period using state-dependent second moments of excess returns. The CHJM is computed as the time-series average of a state-by-state quadratic form, where the conditional pricing error vector is weighted by the inverse of the conditional second-moment matrix of returns, both estimated using ridge regression with Legendre polynomial basis functions of

4.6.1. *Empirical Results*

Table 6 presents the results of the cross-sectional asset pricing tests using 20 economy-industry portfolios as test assets.[31] These portfolios align naturally with the competitive structure where firms compete internationally within industries. For each specification (or model), performance is evaluated using the cross-sectional adjusted R^2 and the relevant HJ measure. Following Jagannathan and Wang (1996), this paper simulates *p*-values to test whether UHJD/UHJM is statistically significant. A bootstrap method is used to compute *p*-values for CHJM.

For the broad sample of developed and other markets, the top panels of Table 6 present the results of a benchmark world CAPM model. The table shows that for the optimal weighting matrix, the SDF loading for GMKT is approximately 0.038, while its factor price is roughly 0.804%. Both estimates are statistically significant at the 1% level. The cross-sectional adjusted R^2 is nearly 0.043 and the UHJD is approximately 0.320 with a simulated *p*-value of approximately 0.056. The UHJM is comparable with an estimate of roughly 0.313 and a simulated *p*-value of roughly 0.043.

The bottom panels of Table 6 show the results of the multifactor model, which substantially improves pricing performance compared to the world CAPM.[32] The cross-sectional adjusted R^2 is roughly 0.411 and the UHJM is approximately 0.411 with a simulated *p*-value of roughly 0.218. Figure 5 shows the cross-sectional performance of the mean betas in explaining average excess equity returns, revealing a positive relation for each of the priced factors. For the optimal weighting

the conditioning instruments. This metric provides a conditional analogue to the unconditional HJ metric (UHJM) and allows pricing performance to be assessed across varying competitive states without requiring direct minimization of a conditional HJ criterion. Crucially, UHJM and CHJM are implemented to evaluate the same asset-pricing model. The difference lies only in the evaluation method. UHJM measures average mispricing assuming constant risk premia. CHJM measures mispricing allowing risk premia to differ across states. Hence the difference between the two metrics reflects the economic importance of state dependence, not overfitting or added complexity.

[31] Appendix A presents additional details of this paper's economy-industry test portfolios.

[32] As a robustness check, Table B.6 and Figure B.4 in Appendix B shows that the multifactor model maintains superior performance over the world CAPM when evaluated using economy-size portfolios rather than economy-industry portfolios.

matrix, the SDF loading for GMKT is approximately −0.002 and no longer statistically significant at the 10% level or less. In comparison, the IAROE factor dominates with an SDF loading of roughly 0.240 and a factor price of 1.118%. Both estimates are statistically significant at the 1% level. The SIZE and CRX factors also show significant SDF loadings and factor prices.

Table 6 also presents results using developed markets only, which allows comparison to benchmark models designed for segmented markets (e.g., world Fama-French five factor, or world FF5).[33] The setting of developed markets also allows for less noise, and a cleaner separation of mechanisms in estimation. For developed markets only, the multifactor model exhibits substantially improved performance compared to that for developed and other markets: the cross-sectional adjusted R^2 increases to approximately 0.567, while the UHJM declines to 0.390 with a simulated p-value of roughly 0.169. This performance substantially exceeds that of the world CAPM, which produces a *negative* adjusted R^2 of −0.018 and UHJM of 0.299 with a simulated p-value of approximately 0.057.

In developed markets, the IAROE factor becomes even more dominant, while the influence of the SIZE factor diminishes. Compared to the estimates for developed and other markets, the SDF loading for the IAROE factor increases to 0.289 and the SDF loading for the SIZE factor declines to 0.082. Both estimates are significant at the 1% level. While the factor price of IAROE increases to 1.535%, remaining significant at the 1% level, the factor price of SIZE declines to 0.021%, and is no longer significant at the 10% level or less. These findings suggest that in developed markets, competitive displacement operates primarily through product pricing rather than firm reach and scale.[34]

For developed markets only, the SDF loading evidence complements the time-series

[33] See fn. 8.
[34] In Appendix B, Figure B.3 presents evidence that reinforces these conclusions.

diagnostic evidence in Table 5 by showing how contamination operates within the pricing kernel itself. Specifically, the loading for GMKT becomes significantly negative at roughly −0.028 with a factor price of approximately 0.439% (compared to 0.795% under the world CAPM). Both estimates are statistically significant at the 1% level.

The negative SDF loading for GMKT is a diagnostic outcome of factor contamination. GMKT is value-weighted, so it is disproportionately driven by dominant firms. Once displacement risk is explicitly controlled for, the SDF loading on GMKT reveals how value-weighting contributes to contamination: the remaining variation in GMKT is tilted toward winner capture through dominant firms. This residual component rises in high–marginal-utility states, when dominant firms capture market share and elevate the value-weighted return even as displacement losses concentrate among vulnerable firms. Therefore, in a multifactor model, the SDF must load negatively on GMKT to price assets correctly. At the same time, the remaining variation in GMKT still carries priced aggregate risk because of a positive correlation with other priced factors, so the GMKT factor price remains positive but is materially attenuated. In other words, competitive displacement accounts for a substantial share of what appears as "market risk" in traditional models.

For developed markets only, the GMM specification, made conditional by imposing moment orthogonality on the three principal component instruments, achieves a CHJM of 0.032 with a bootstrapped *p*-value of roughly 0.901. This near-zero distance indicates that only a very small pricing error remains once competitive conditions are allowed to vary across states. Moreover, the Hansen J-statistic fails to reject the overidentifying restrictions, indicating that the conditional moment restrictions implied by the model are jointly satisfied.

To illustrate the practical meaning of this performance, Table 7 and Figure 7 examine cross-

sectional fit and pricing errors across normal (377 months) and displacement periods (43 months). Table 7 examines pure cross-sectional estimates using regressions of mean portfolio returns on mean factor betas for 20 economy-industry portfolios (developed markets only). The world CAPM shows a weak cross-sectional fit during normal periods (R^2 roughly equal to 0.001) and displacement periods (R^2 approximately equal to 0.053). In comparison, the world FF5 shows modest fit during normal periods (R^2 roughly equal to 0.186) that increases to approximately 0.339 during displacement.

Compared to these benchmark models, the world multifactor model exhibits substantially better cross-sectional fit that improves during displacement periods. The adjusted R^{2_2} is roughly 0.457 during normal periods and increases to roughly 0.920 during displacement episodes. For context, using the full sample period, Table 6 reports an adjusted R^2 of approximately 0.567; a value that falls between 0.457 and 0.920. The state-specific results reveal what the full-sample statistic obscures: the model's fit is not merely adequate on average but actually strengthens during periods of severe competitive displacement.

Figure 7 translates these fit statistics into mean absolute pricing errors (MAPE). In both panels, portfolios are grouped by industry profitability dispersion quintiles. Panel A presents MAPE during normal periods (left image) and displacement periods (right image). During normal periods, all models exhibit moderate pricing errors, with the world multifactor model showing the lowest MAPE across all dispersion groups. During displacement periods, the pattern diverges sharply: the world CAPM and world FF5 exhibit substantially elevated MAPE, with deterioration concentrated in high-dispersion portfolios where competitive displacement is most active. The multifactor model maintains stable, low MAPE across all groups. Panel B quantifies these differences. The benchmark models deteriorate from normal to displacement periods for high-

dispersion portfolios (left image), and exhibit substantially larger errors than the multifactor model during displacement periods (right image).

Taken together, the evidence in Table 7 and Figure 7 demonstrates that the near-zero conditional pricing error of the multifactor model arises because the model maintains stable pricing accuracy across competitive states, achieving a near-perfect cross-sectional fit during displacement episodes when traditional models deteriorate. The concentration of pricing errors in high-dispersion portfolios further validates the factor contamination mechanism: traditional models fail precisely where competitive displacement is most active.

5. Concluding Remarks

What does a value-weighted market return actually measure? As index concentration has reached historic highs, this question has become increasingly important.[35] When index weights mechanically tilt toward a narrow set of winners, the market return reflects the performance of dominant firms in product market competition. As a result, the value-weighted excess market return is not a clean proxy for systematic risk. Instead, it is an endogenous mixture of aggregate economic exposure and competitive displacement across firms.

This paper's empirical evidence reveals that competitive displacement plays a central role in determining international equity risk premia, generating novel systematic patterns. Portfolios constructed using industry-adjusted profitability exhibit extreme nonlinearity near displacement: excess returns rise sharply as relative profitability approaches zero, reflecting elevated displacement risk for the most vulnerable firms. These portfolios also form the basis of an IAROE factor which produces a mean monthly excess return of 0.804% and Sharpe ratio of 1.123.

[35] See Jason Zweig, "What You Should Do About the Stock Market's Giant Problem," *The Wall Street Journal*, February 7, 2025.

Displacement risk contaminates the global market factor in a predictable, state-dependent way. During the six identified episodes of severe competitive disruption, market betas for a high-minus-low industry profitability dispersion portfolio (i.e., a displacement-sensitive portfolio) shift materially, but this instability disappears once IAROE and other factors are included in the time-series specification. The findings suggest that the shifting market exposure is reassigned to the IAROE factor in a manner consistent with factor contamination.

This paper's theoretical model explains how this factor contamination emerges during global competition. Within a Ricardian framework, supply-side cost shocks generate competitive displacement that fundamentally alters the mapping between firm payoffs and the global market factor. Value-weighting amplifies this distortion by assigning a disproportionate weight to dominant firms that capture market share during displacement episodes, while underweighting vulnerable firms that bear the largest losses.

Building on these insights, the paper develops a conditional world multifactor model that explicitly prices displacement risk and conditions on time-varying competitive states. For developed markets, the model achieves a conditional Hansen–Jagannathan metric of 0.032, indicating that essentially no systematic pricing error remains once competitive conditions are allowed to vary across states. Importantly, the model maintains stable pricing accuracy across both normal periods and displacement episodes, achieving a near-perfect cross-sectional fit precisely when benchmark models deteriorate.

By integrating lessons from international trade and industrial organization, this paper establishes that competition in global product markets shapes not only firm outcomes but the structure of systematic risk itself.

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Table 1. A Ricardian Model of International Asset Pricing: Economic Characteristics

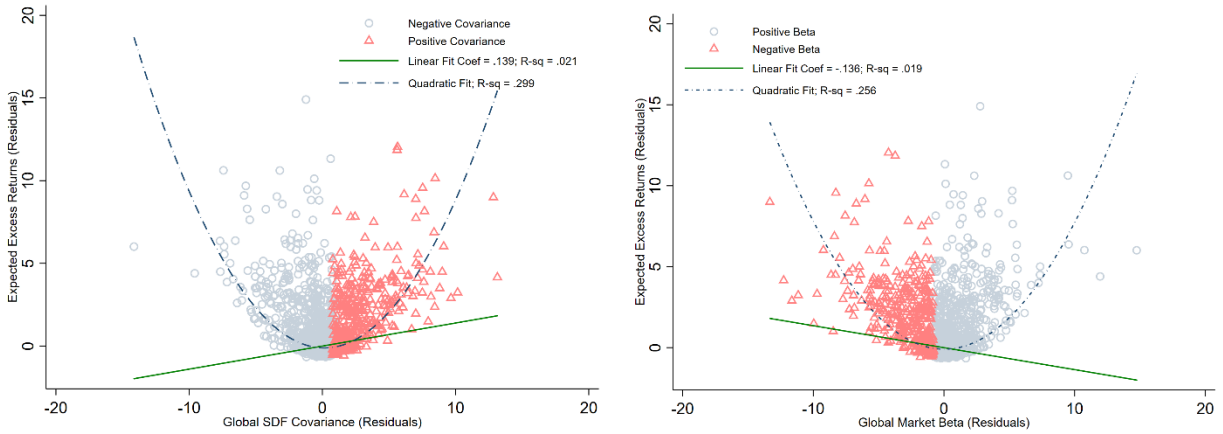
This table presents the model parameters α, and β_p, along with moments for the characteristics $\ln(Y_{i,1})$, $\ln(T_i)$, $\ln(d_n)$, and $c_{i,1}$, of the 19 economies used in Eaton and Kortum (2002) under the case of strong comparative advantage (θ = 3.60). Each moment belongs to a normal distribution with mean μ and standard deviation σ. Jointly distributed characteristics exhibit correlation ρ. Bilateral geographic barriers (in logs) are simulated with a beta distribution using a scale parameter of the simulated $\ln(d_n)$, and a shape parameter of 2. Bilateral geographic barriers always satisfy the triangle inequality of cross-border arbitrage. This table also presents two additional global model parameters κ and $\rho_{\eta\nu}$. There are 5 trials (representing 5 global economic systems). 30 simulated economies are drawn from the distribution of economic characteristics for each trial. Simulated firms arise endogenously as a result of imperfect global competition in 500 different industries at time t = 1 (serving 15,000 possible economy-industry markets). Across all trials, there is a total of 6,774 simulated firms with an average of roughly 1,355 firms per trial. Stochastic shocks are generated for each simulated firm to produce 100 outcome profiles at time t = 2, resulting in a total of 677,400 numerical simulation outcome profiles under global competition. The descriptions of the model parameters, macroeconomic characteristics, and model outcomes are presented in Table A.1. Estimated equity return generating parameters and moment matching performance are presented in Table C.1.

Parameter Values and Simulation Moments [Comparative Advantage, θ = 3.60]			
α	0.130	κ	0.040
β_p	0.210	$\rho_{\eta\nu}$	0.400
$c_{i,1}$	μ = 9.044; σ = 1.919	$\ln(Y_{i,1})$	μ = 26.664; σ = 1.306
$\ln(d_n)$	μ = 0.297; σ = 0.149	$\ln(T_i)$	μ = 7.135; σ = 0.563
$c_{i,1}, \ln(d_n)$	ρ = −0.086	$c_{i,1}, \ln(Y_{i,1})$	ρ = 0.112
$c_{i,1}, \ln(T_i)$	ρ = 0.435	$\ln(d_n), \ln(Y_{i,1})$	ρ = −0.713
$\ln(d_n), \ln(T_i)$	ρ = −0.667	$\ln(Y_{i,1}), \ln(T_i)$	ρ = 0.876

Figure 1. The Contamination of Global Single-Factor Proxies for the Stochastic Discount Factor

This figure presents a regression fit (using residuals to acknowledge trial fixed effects) for the relation between a single-factor proxy for the stochastic discount factor (SDF) and expected excess equity returns for simulated firms. For each panel, the image on the left presents results for global consumption growth as the single-factor proxy, while the image on the right presents results for the value-weighted global equity market return as the (inverse) single-factor proxy. Each image either distinguishes contrarian simulation outcomes (hollow triangle markers) from conventional simulation outcomes (hollow circle markers), or insignificant market betas (hollow triangle markers) from simulation outcomes with statistically significant market betas (hollow circle markers). The model parameters, along with moments for the macroeconomic characteristics are shown in Table 1. The descriptions of the model parameters, macroeconomic characteristics, and model outcomes are presented in Table A.1.

Panel A



Panel B

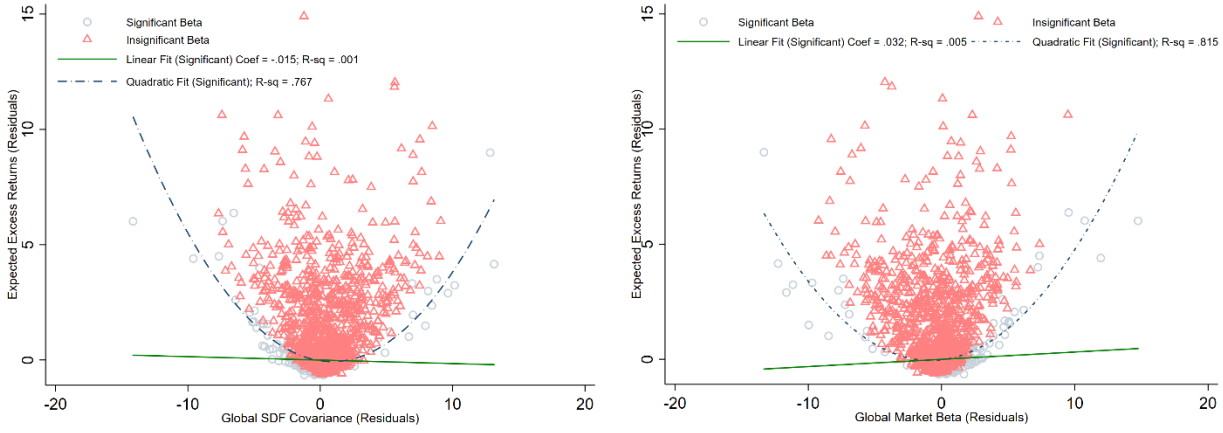
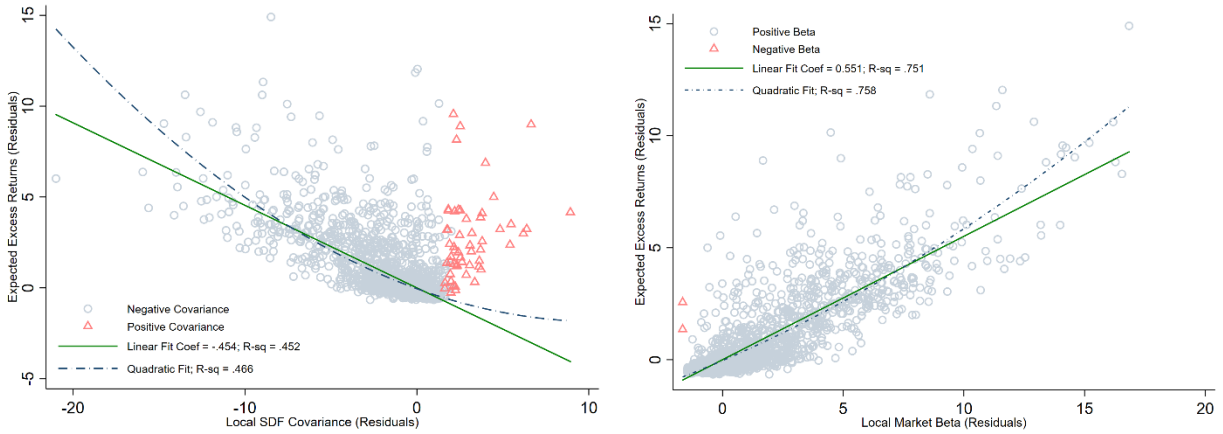


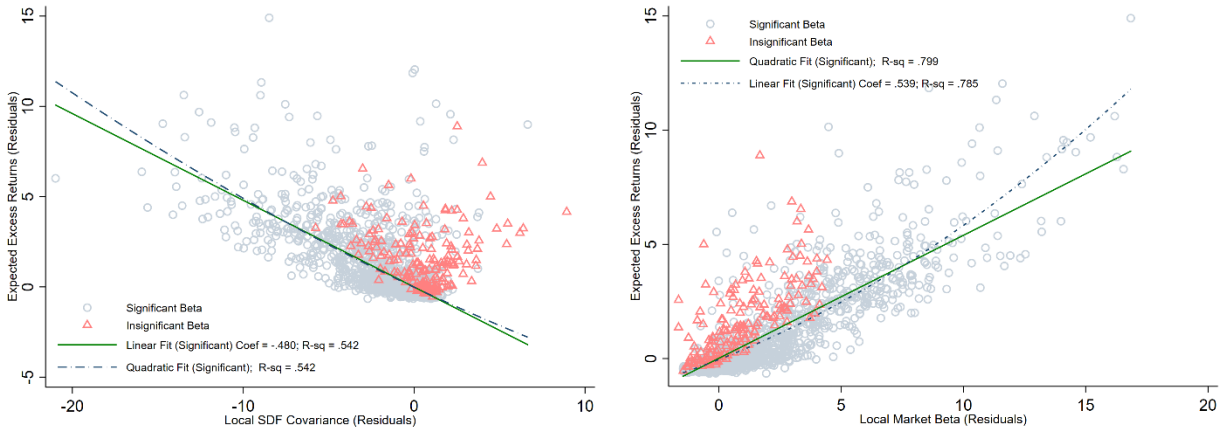
Figure 2. Imperfect Competition as the Driver of Global Factor Contamination

This figure presents a regression fit (using residuals to acknowledge trial fixed effects) for the relation between a single-factor proxy for the stochastic discount factor (SDF) and expected excess equity returns for simulated firms. In Panels A and B, the image on the left presents results for local consumption growth as the single-factor proxy, while the image on the right presents results for the value-weighted local equity market return as the (inverse) single-factor proxy. In Panel C, both images present results for the equal-weighted global equity market return as the single-factor proxy. Each image either distinguishes contrarian simulation outcomes (hollow triangle markers) from conventional simulation outcomes (hollow circle markers), or insignificant market betas (hollow triangle markers) from simulation outcomes with statistically significant market betas (hollow circle markers). The model parameters, along with moments for the macroeconomic characteristics are shown in Table 1. The descriptions of the model parameters, macroeconomic characteristics, and model outcomes are presented in Table A.1.

Panel A



Panel B



Panel C

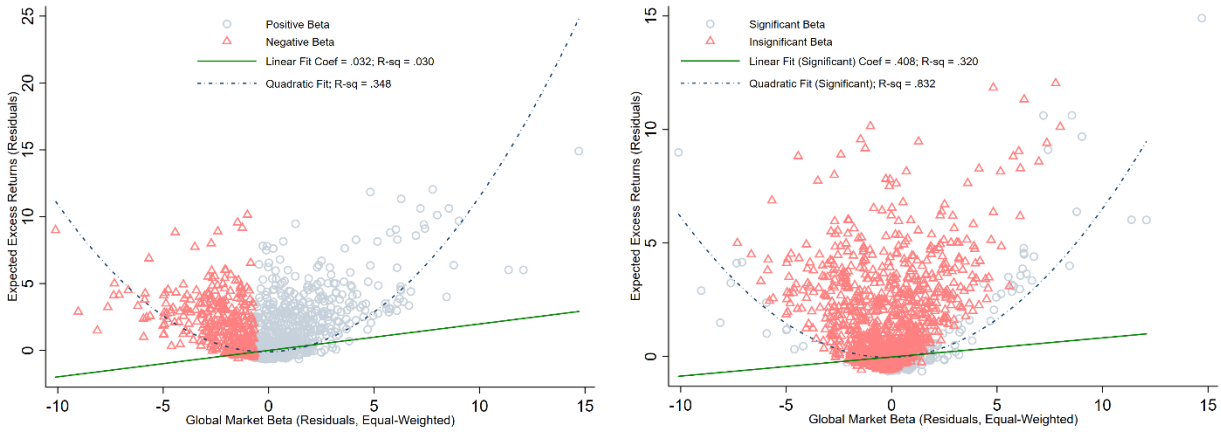

Positive Beta
Negative Beta
Linear Fit Coef = .032; R-sq = .030
Quadratic Fit; R-sq = .348
Expected Excess Returns (Residuals)
Global Market Beta (Residuals, Equal-Weighted)
Significant Beta
Insignificant Beta
Linear Fit (Significant) Coef = .408; R-sq = .320
Quadratic Fit (Significant); R-sq = .832
Expected Excess Returns (Residuals)
Global Market Beta (Residuals, Equal-Weighted)

Table 2. Negative and Insignificant Market Betas for Simulated Firms

This table presents logit regression results for the sample of simulated firms where the left-hand-side (LHS) variable is a binary indicator equal to one if the simulated firm exhibits a negative global market beta (in columns 1 to 6), or a binary indicator equal to one if the simulated firm exhibits a negative global market beta or a global market beta that is not statistically significant. The model parameters, along with the moments for the macroeconomic characteristics are shown in Table 1. The descriptions of the model parameters, macroeconomic characteristics, and model outcomes are presented in Table A.1.

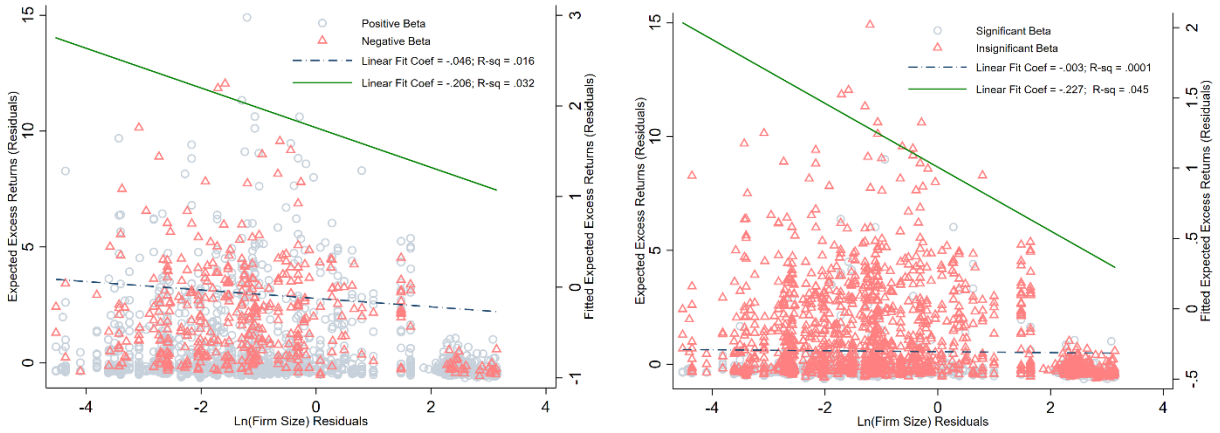
$pm_{ki,1}$	−0.409	−0.407	−0.406	−0.403	−0.404	−0.399	−0.404
	(0.012)**	(0.012)**	(0.012)**	(0.012)**	(0.012)**	(0.012)**	(0.011)**
$\ln\left(2\sum_{n\in\Lambda_{ki,1}} x_{kn,1}\right)$	−0.035	−0.038	−0.033	−0.035	−0.037	−0.039	−0.040
	(0.004)**	(0.005)**	(0.004)**	(0.005)**	(0.005)**	(0.005)**	(0.005)**
$c_{i,1}$		0.003			0.001	0.006	0.006
		(0.005)			(0.005)	(0.004)	(0.004)
$\ln(Y_{i,1})$		−0.011			−0.008	−0.015	−0.013
		(0.009)			(0.008)	(0.007)*	(0.007)*
$\ln(d_n)$		−0.021			−0.021	−0.026	−0.026
		(0.008)**			(0.008)**	(0.005)**	(0.006)**
I(CRX Portfolio = 2)				−0.031		−0.034	−0.038
				(0.016)+		(0.013)**	(0.013)**
I(CRX Portfolio = 3)				−0.061		−0.067	−0.072
				(0.013)**		(0.011)**	(0.012)**
I(CRX Portfolio = 4)				−0.060		−0.064	−0.069
				(0.014)**		(0.015)**	(0.015)**
I(CRX Portfolio = 5)				−0.085		−0.092	−0.099
				(0.015)**		(0.014)**	(0.015)**
Trial dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Home economy included	Yes	Yes	No	No	No	No	No
Number of sim. firms	6774	6774	6480	6480	6480	6480	6480
Model *p*-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Coefficients are presented as marginal effects. Robust delta-method standard errors which cluster at the trial-economy level are reported in parentheses. Model *p*-value shows the result for a test that all of the coefficients (excluding the constant) are jointly zero. +, *, ** denote statistical significance at the 10%, 5% and 1% levels.

Figure 3. Characteristics of Simulated Firms and Expected Excess Equity Returns

This figure presents a regression fit (using residuals to acknowledge trial fixed effects) for the relation between the characteristics of simulated firms and the expected excess equity returns for those simulated firms. Panel A presents results for $\ln\left(2\sum_{n\in\Lambda_{ki,1}} x_{kn,1}\right)$ or ln (*Firm Size*), while Panel B presents results for $pm_{ki,1}$ or *Profitability*. For each panel, the image on the left distinguishes negative global market betas (hollow triangle markers) from positive global market betas (hollow circle markers). Each image shows two y-axes. The y-axis on the left represents expected excess equity returns for the simulation outcomes, while the y-axis on the right represents the fitted expected excess equity returns for the regressions. The model parameters, along with moments for the macroeconomic characteristics are shown in Table 1. The descriptions of the model parameters, macroeconomic characteristics, and model outcomes are presented in Table A.1.

Panel A: Firm Size



Panel B: Profitability

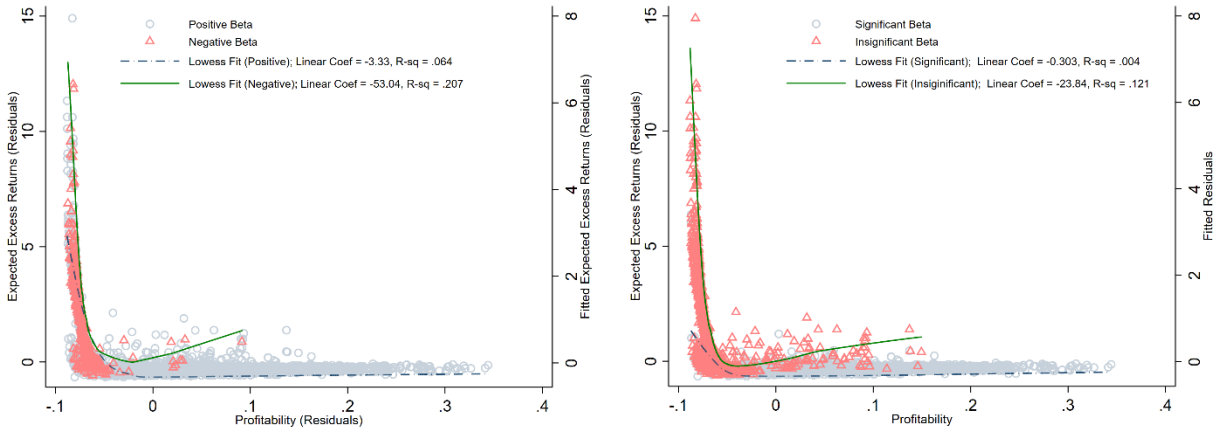


Table 3. Portfolios and Factors

This table presents the summary statistics for portfolios, and factors. The sample period is from July 1989 to June 2024. *Market value of equity* is the total market capitalization of a firm's equity (in June 2024 US dollars). *Excess return* is the monthly return (in US dollars) to buying the stock at time $t - 1$ and then selling it at time t, in excess of the risk-free rate. *Value-weighted excess return* is the weighted mean of *Excess return* for a portfolio where the weight of each stock is its *Market value of equity*. Single-sorted portfolios are created in June of year y for the evaluation of monthly returns from July of year y to June of year $y + 1$. Five portfolios are created based on quintiles for each sorting characteristic (*Market value of equity*, SIZE; *Industry-adjusted return on equity*, IAROE; *Technology*, TECH; *Trade protection*, TDPRT; *Industry profitability dispersion*, IDISP; and *Mean currency excess return*, CRX). *Industry-adjusted return on equity* is the residual from a regression of return on equity (net income divided by total equity) on (two-digit standard industry classification, SIC, code) industry fixed effects for all firms using the full data extraction period (January 1975 to March 2025). *Technology* is a measure of absolute advantage proxied by current gross domestic product (in US dollars). *Trade protection* is a measure of trade protection proxied by the (interpolated) weighted average of the import tariff rate across all products in an economy. *Industry profitability dispersion* is the interquartile range for return on equity within an industry. *Mean currency excess return* is the annual average of the currency excess return in an economy, where the currency excess return is computed as the monthly return (in US dollars) to buying a foreign currency in the forward market (at the forward rate) at time $t - 1$ and then selling it in the spot market (at the spot rate) at time t. For TECH, TDPRT, IDISP and CRX, single-sorted portfolios for portfolio year y are based on the year $y - 1$ value for the characteristic of the economy where the firm is listed. These single-sorted portfolios are used to construct factors as Q5 – Q1 long-short factor mimicking portfolios. Single-sorted portfolios for SIZE and IAROE are created in June of year y for summary statistics (using *Market value of equity* in June of year y and *Industry-adjusted return on equity* in December of year $y - 1$). Double-sorted portfolios for SIZE and IAROE are also created in June of year y for evaluation of monthly returns from July of year y to June of year $y + 1$. Two portfolios for SIZE are first created based on the median cutoff of *Market value of equity* in June of year y. Within each of these SIZE portfolios, five portfolios for IAROE (P1 to P5 for the low SIZE portfolio, and P6 to P10 for the high SIZE portfolio) are created based on quintiles for *Industry-adjusted return on equity* in December of year $y - 1$. These double-sorted portfolios are used to construct factors as long-short portfolio return averages. The SIZE factor is the average return of P6 to P10 (SIZE2) minus the average return of P1 to P5 (SIZE1). The IAROE factor is the average return of P1 and P6 (IAROE1) minus the average return of P2 and P7 (IAROE2). *Global market factor* (GMKT) is the monthly return (in US dollars) of the global Morgan Stanley Capital International (MSCI) index in excess of the risk-free rate. *Local market factor* (LMKT) is the weighted mean of *Excess return* for all firms in an economy where the weight of each stock is its *Market value of equity*. Panel A shows summary statistics for the double-sorted portfolios. Panel B presents summary statistics for the single-sorted IDISP portfolios. Panel C shows summary statistics for the global factors, and Panel D presents the pairwise correlations for all global factors. Newey and West (1987) standard errors with optimal lag selection, are reported in Panels A, B, and C. Variable descriptions are presented in Table A.1.

Panel A: Firm Characteristic Portfolios

Double-Sorted Portfolio	P1	P2	P3	P4	P5	SIZE1
Value-weighted excess return	3.816	2.445	2.082	2.408	2.951	2.741
	(0.417)	(0.302)	(0.229)	(0.283)	(0.323)	(0.297)
Market value of equity (mean)	47.551	54.631	58.881	60.915	60.913	
Industry-adjusted return on equity (mean)	−5140.73	229.67	163.32	145.23	883.57	
Number of firms (mean)	717	859	924	911	845	
Average single-sorted SIZE portfolio	1.87	2.08	2.16	2.17	2.12	
Average single-sorted IAROE portfolio	1.00	1.48	2.50	3.67	4.86	
Average single-sorted TECH portfolio	4.31	4.27	4.31	4.30	4.32	
Average single-sorted TDPRT portfolio	2.29	2.58	2.66	2.60	2.44	
Average single-sorted CRX portfolio	2.83	2.84	2.83	2.85	2.84	
Double-Sorted Portfolio	P6	P7	P8	P9	P10	SIZE2
Value-weighted excess return	1.021	0.784	0.875	1.011	1.235	0.985
	(0.214)	(0.177)	(0.169)	(0.194)	(0.193)	(0.175)
Market value of equity (mean)	2985.02	3573.71	4242.63	4911.70	6104.18	
Industry-adjusted return on equity (mean)	366.66	315.34	106.90	118.94	946.92	
Number of firms (mean)	1961	2031	2036	2052	2062	
Average single-sorted SIZE portfolio	4.18	4.31	4.35	4.36	4.35	
Average single-sorted IAROE portfolio	1.27	2.23	3.12	4.04	5.00	
Average single-sorted TECH portfolio	4.60	4.58	4.52	4.48	4.49	
Average single-sorted TDPRT portfolio	2.42	2.49	2.46	2.42	2.37	
Average single-sorted CRX portfolio	2.77	2.77	2.81	2.86	2.83	
	IAROE1	IAROE2	IAROE3	IAROE4	IAROE5	
Value-weighted excess return	2.419	1.614	1.478	1.710	2.093	
	(0.305)	(0.227)	(0.190)	(0.224)	(0.232)	

Panel B: Industry Profitability Dispersion Portfolios

IDISP Portfolio	Q1	Q2	Q3	Q4	Q5
Value-weighted excess return	0.644	0.695	1.123	0.922	1.117
	(0.145)	(0.158)	(0.172)	(0.185)	(0.219)
Market value of equity (mean)	2726.88	1658.66	1733.96	2229.25	2001.65
Industry-adjusted return on equity (mean)	21.14	−84.29	−41.58	−1.23	2.16
Number of firms (mean)	4389	4874	4832	5385	4781
Average single-sorted SIZE portfolio	3.53	3.23	3.22	3.26	3.13
Average single-sorted IAROE portfolio	2.75	2.83	2.90	3.11	3.34
Average single-sorted TECH portfolio	4.32	4.31	4.41	4.50	4.52
Average single-sorted TDPRT portfolio	2.42	2.71	2.74	2.60	2.33
Average single-sorted CRX portfolio	2.84	2.80	2.77	2.81	2.81

Panel C: Global Factor Summary Statistics

Factor	**GMKT**	**SIZE**	**IAROE**	**TECH**	**TDPRT**	**CRX**
Mean	0.558	1.755	0.804	−0.318	0.233	0.928
Mean (annualized)	6.700	21.065	9.650	−3.814	2.790	11.137
Standard error (annualized)	0.666	0.599	0.427	1.509	1.220	1.933
Standard deviation (annualized)	16.164	10.316	8.590	16.065	29.086	13.940
Autocorrelation (1)	0.073	0.163	0.172	0.235	−0.014	0.575
Skewness	−0.433	0.184	0.760	−0.880	2.139	1.608
Kurtosis	5.190	5.847	7.888	6.682	27.071	8.147
Reward-risk ratio (Sharpe, annualized)	0.414	2.042	1.123	−0.237	0.096	0.799

Panel D: Global Factor Correlations

	GMKT	SIZE	IAROE	TECH	TDPRT	CRX
GMKT	1.0000					
SIZE	−0.1472*	1.0000				
IAROE	0.2699*	0.2971*	1.0000			
TECH	0.1402*	−0.2404*	0.0903	1.0000		
TDPRT	−0.0369	0.2043*	0.0045	−0.0356	1.0000	
CRX	0.0299	−0.0264	−0.0410	−0.0149	0.0018	1.0000

Table 4. Explaining Fim Size and Industry Dispersion Anomalies

This table presents results for time-series portfolio regressions. For each regression, Newey and West (1987) standard errors with optimal lag selection are estimated with absolute *t*-statistics reported in parentheses. +, *, ** denote statistical significance at the 10%, 5% and 1% levels. The sample period is from July 1989 to June 2024. The variable definitions [descriptions] are presented in Table 3 [Table A.1].

Panel A: World CAPM

SIZE Portfolio	Q1	Q2	Q3	Q4	Q5	Q1 – Q5
Market factor	0.472	0.478	0.478	0.529	0.680	−0.209
	(10.661)**	(25.802)**	(30.154)**	(20.079)**	(13.266)**	(4.335)**
Alpha	2.326	1.463	0.977	0.789	0.469	1.856
	(7.312)**	(8.260)**	(6.568)**	(6.680)**	(5.360)**	(6.673)**
Number of periods	420	420	420	420	420	420

IDISP Portfolio	Q1	Q2	Q3	Q4	Q5	Q5 – Q1
Market factor	0.761	0.732	0.805	0.713	0.801	0.040
	(20.686)**	(19.908)**	(22.985)**	(12.104)**	(26.121)**	(0.970)
Alpha	0.219	0.286	0.674	0.524	0.670	0.451
	(3.421)**	(3.246)**	(5.858)**	(3.836)**	(3.953)**	(2.584)**
Number of periods	420	420	420	420	420	420

Panel B: World Multifactor

SIZE Portfolio	Q1	Q2	Q3	Q4	Q5	Q1 – Q5
Market factor	0.491	0.516	0.498	0.534	0.650	−0.159
	(11.988)**	(17.701)**	(15.976)**	(14.812)**	(20.106)**	(3.657)**
IAROE	0.319	0.118	0.133	0.091	0.137	0.181
	(2.313)*	(2.014)*	(1.738)+	(1.364)	(1.859)+	(2.435)*
Alpha	1.017	0.352	0.091	0.306	0.520	0.498
	(5.477)**	(3.781)**	(0.822)	(2.925)**	(4.851)**	(2.134)*
Number of periods	420	420	420	420	420	420

IDISP Portfolio	Q1	Q2	Q3	Q4	Q5	Q5 – Q1
Market factor	0.770	0.746	0.770	0.651	0.733	−0.037
	(30.896)**	(18.787)**	(27.524)**	(13.750)**	(25.789)**	(1.389)
IAROE	−0.109	−0.102	0.162	0.290	0.388	0.498
	(2.111)*	(1.826)+	(3.573)**	(2.593)**	(4.697)**	(5.028)**
Alpha	0.522	0.368	0.551	0.476	0.452	−0.071
	(5.313)**	(3.628)**	(5.986)**	(4.563)**	(3.213)**	(0.433)
Number of periods	420	420	420	420	420	420

Figure 4. Conditioning Instruments During Normal and Displacement Periods

This figure presents a time-series plot of the twelve-month moving average for the conditioning instruments used in this paper. The conditioning instruments are three principal component scores (PC1, PC2, and PC3) derived from the dynamics of the technology factor (TECH) and the trade protection factor (TDPRT). Six major episodes of product market displacement are identified as structural breaks: the Mexican peso crisis (MPS), the Asian financial crisis (AFC), the dot-com bust (DCB), the great trade collapse following the global financial crisis (GFC), the taper tantrum (TTM), and the US-China trade war (TRD). The sample period is from July 1989 to June 2024. The variable definitions [descriptions] are presented in Table 3 [Table A.1].

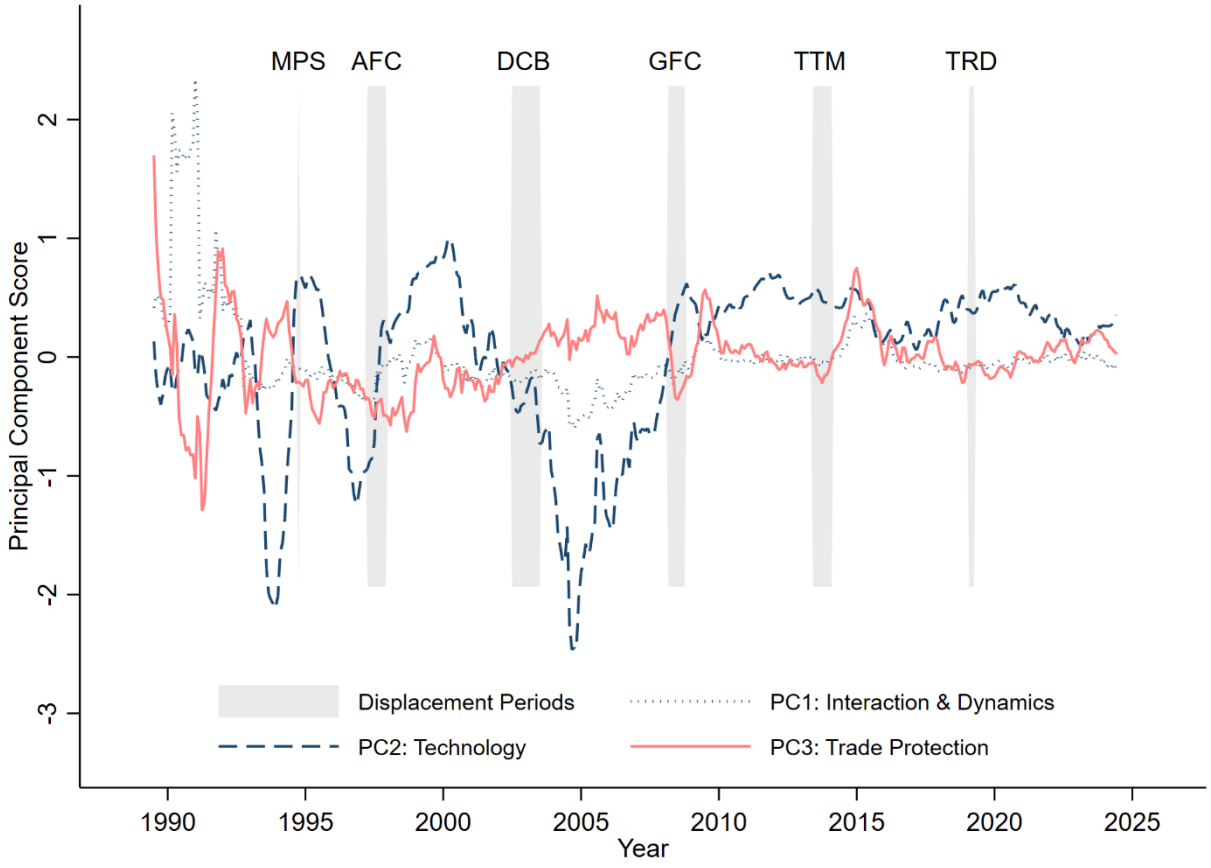


Table 5. Explaining the Industry Dispersion Anomaly During Normal and Displacement Periods

This table presents results for time-series portfolio regressions. For each regression, Newey and West (1987) standard errors with optimal lag selection are estimated with absolute *t*-statistics reported in parentheses. +, *, ** denote statistical significance at the 10%, 5% and 1% levels. The sample period is from July 1989 to June 2024. The variable definitions [descriptions] are presented in Table 3 [Table A.1].

IDISP Portfolio	Q5 – Q1		Q5 – Q1		
Market factor	0.006	0.204	−0.057	0.012	−0.051
	(0.148)	(3.456)**	(1.974)*	(0.128)	(1.756)+
IAROE			0.457	0.862	0.454
			(4.704)**	(3.775)**	(4.471)**
IAROE (displacement margin)					0.498
					(2.258)*
Alpha	0.489	0.362	−0.078	−0.216	−0.083
	(2.535)*	(1.335)	(0.440)	(0.620)	(0.492)
Alpha (displacement margin)					−0.090
					(0.257)
Factors included	GMKT		GMKT, SIZE, IAROE, TECH, TDPRT, CRX		
Period type	Normal	Displacement	Normal	Displacement	All
Number of periods	377	43	377	43	420

Table 6. World Multifactor Model (Ricardian): Performance Tests

This table presents results for asset pricing tests using a generalized method of moments (GMM) procedure with Hansen-Jagannathan (HJ) weights and optimal weights. The test assets are 20 economy-industry portfolios. For developed and other markets, the sample period is from May 1991 to June 2024. For developed markets only, the sample period is from July 1989 to June 2024. The variable definitions [descriptions] are presented in Table 3 [Table A.1]. Summary statistics for the economy-industry portfolios are shown in Table A.2.

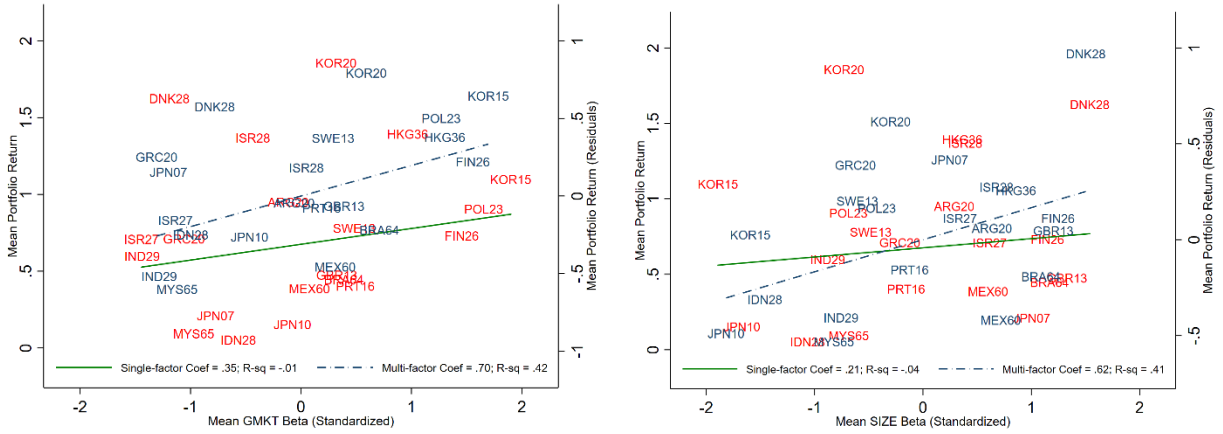
Factor	**GMKT**	**SIZE**	**IAROE**	**CRX**			
World CAPM One-step GMM (HJ) Estimates					A.R-sq		UHJD
			Developed and Other Markets				
Factor price	0.814				0.043		0.320
	[0.000]**						[0.056]+
SDF loading	0.038						
	[0.000]**						
World CAPM Two-step GMM (Optimal) Estimates					A.R-sq		UHJM
			Developed and Other Markets				
Factor price	0.804				0.043		0.313
	[0.000]**						[0.043]*
SDF loading	0.038						
	[0.000]**						
			Developed Markets Only				
Factor price	0.795				−0.018		0.299
	[0.000]**						[0.057]+
SDF loading	0.037						
	[0.000]**						
World Multifactor Two-step GMM (Optimal) Estimates					A.R-sq	Hansen J	UHJM/CHJM
			Developed and Other Markets				
Factor price	0.992	0.827	1.118	1.408	0.411	14.908	0.411
	[0.000]**	[0.000]**	[0.000]**	[0.000]**		[1.000]	[0.218]
SDF loading	−0.002	0.160	0.240	0.087			0.343
	[0.555]	[0.000]**	[0.000]**	[0.000]**			[0.400]
			Developed Markets Only				
Factor price	0.439	0.021	1.535	1.025	0.567	15.659	0.390
	[0.000]**	[0.579]	[0.000]**	[0.000]**		[1.000]	[0.169]
SDF loading	−0.028	0.082	0.289	0.057			0.032
	[0.000]**	[0.000]**	[0.000]**	[0.000]**			[0.901]

I estimate Newey and West (1987) standard errors with optimal lag selection. *p*-values are reported in brackets. UHJD denotes the unconditional Hansen and Jagannathan (1997) distance, defined as the minimized Hansen–Jagannathan–weighted pricing-error criterion. UHJM and CHJM denote the unconditional and conditional Hansen–Jagannathan metrics, respectively, computed as the Hansen–Jagannathan norm of the pricing-error vector evaluated at the optimal GMM estimates. The reported statistics test the null hypothesis that the corresponding pricing-error measure is equal to zero. Hansen J denotes the Hansen (1982) J statistic for the null hypothesis that the overidentifying restrictions are valid. A.R-sq is the adjusted R-squared from a cross-sectional regression of average excess returns on the mean factor exposure (or beta) estimates. +, *, ** denote statistical significance at the 10%, 5% and 1% levels.

Figure 5. Global Multifactor Betas and Economy-Industry Portfolios: Developed and Other Markets

This figure presents a linear regression fit and a scatter plot for the cross-sectional relation between the mean monthly portfolio return and the average generalized method of moments (GMM) estimate of the factor exposure (or beta) for the test assets in a multifactor model. The test assets are the 20 economy-industry portfolios (with plot markers XXXNN where XXX represents the economy code and NN represents the two-digit standard industry classification, SIC, code). There are four factors. Panel A presents results for the mean GMKT and SIZE factor betas, while Panel B shows the results for the mean IAROE and CRX factor betas. Each image shows two y-axes. The y-axis on the left represents the results using a specification limited to the single beta shown on the x-axis, while the y-axis on the right represents the results using a specification with all four mean factor betas. Mean betas on the x-axis are standardized to show consistent estimates across both y-axes. The sample period is from May 1991 to June 2024. The variable definitions [descriptions] are presented in Table 3 [Table A.1]. Summary statistics for the economy-industry portfolios are shown in Table A.2.

Panel A: GMKT and SIZE Factor Betas



Panel B: IAROE and CRX Factor Betas

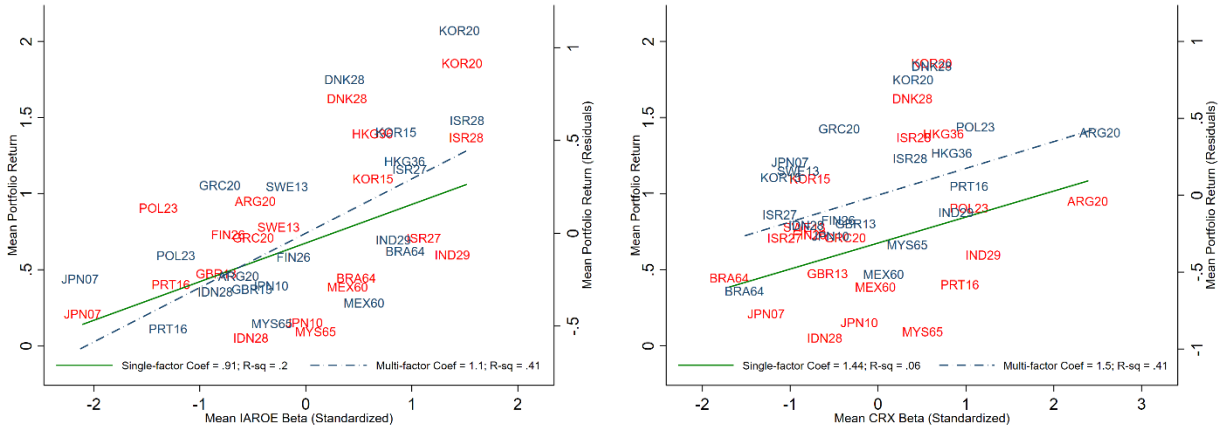


Table 7. Cross-Sectional Pricing Fit During Normal and Displacement Periods

For different pricing models, this table presents cross-sectional regression results for the 20 economy-industry portfolio test assets where the left-hand-side (LHS) variable is the mean monthly portfolio return, and the right-hand-side (RHS) variables are average factor exposures (or betas) for the test assets. In columns 3 and 4, the sample period is from July 1990 to June 2024. In all remaining columns, the sample period is from July 1989 to June 2024. The variable definitions [descriptions] are presented in Table 3 [Table A.1]. Summary statistics for the economy-industry portfolios are shown in Table A.2.

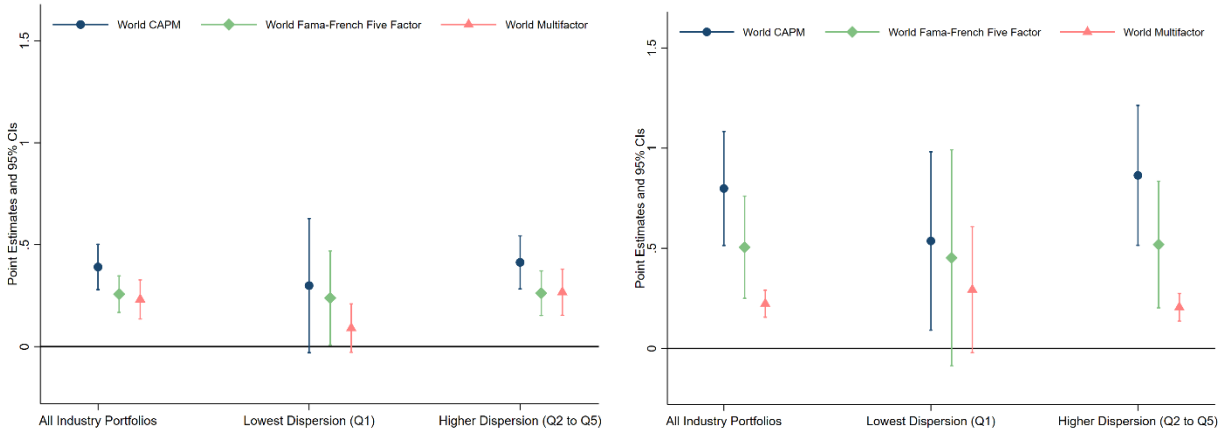
Model	**World CAPM**		**World Fama-French Five Factor**		**World Multifactor**	
Mean market factor beta	0.475	−0.684	0.584	−0.843	0.119	−0.289
	(1.007)	(1.437)	(1.393)	(1.683)	(0.321)	(1.951)+
Mean factor beta 2 (SMB, SIZE)			0.041	0.290	0.772	−0.089
			(0.115)	(0.830)	(1.672)	(0.466)
Mean factor beta 3 (HML, IAROE)			0.459	−1.092	1.485	0.888
			(1.274)	(0.684)	(4.054)**	(4.298)**
Mean factor beta 4 (RMW, CRX)			0.122	−0.146	−0.152	1.297
			(0.637)	(0.477)	(0.167)	(3.680)**
Mean factor beta 5 (CMA)			0.680	−0.773		
			(2.672)*	(0.907)		
Portfolio type			Economy-Industry			
Developed markets only			Yes			
Period type	Normal	Displacement	Normal	Displacement	Normal	Displacement
Number of periods	377	43	365	43	377	43
Number of test portfolios	20	20	20	20	20	20
Adjusted R-sq	0.001	0.053	0.186	0.339	0.457	0.920

Absolute *t*-statistics are reported in parentheses. +, *, ** denote statistical significance at the 10%, 5% and 1% levels.

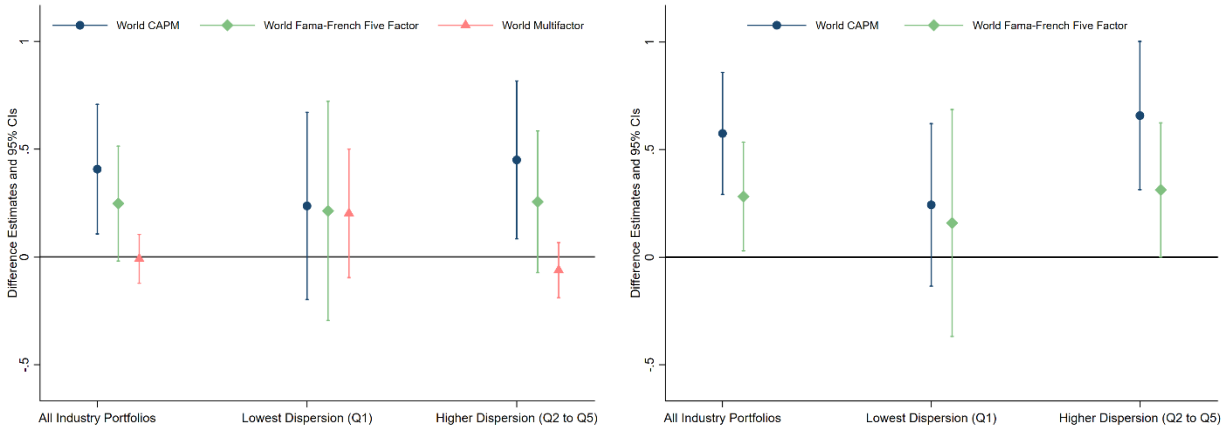
Figure 6. Cross-Sectional Pricing Errors During Normal and Displacement Periods: Developed Markets Only

This figure presents a scatter plot and a confidence interval (CI) range plot for the mean absolute cross-sectional pricing errors. For each test asset, the cross-sectional pricing error is the difference between the mean monthly portfolio return and the expected return using the average factor betas. The test assets are the 20 economy-industry portfolios (developed markets only). Economy-industry portfolios are categorized based on quintiles of *Industry profitability dispersion*. Panel A presents results for the mean absolute pricing error (MAPE) during normal periods (left image) and displacement periods (right image) for different pricing models. Panel B shows the results for the difference between normal periods and displacement periods (left image) and the difference between other pricing models and the world multifactor model during displacement periods (right image). The sample period for the world Fama-French five factor model is from July 1990 to June 2024. The sample period for all other models is from July 1989 to June 2024. The variable definitions [descriptions] are presented in Table 3 [Table A.1]. Summary statistics for the economy-industry portfolios are shown in Table A.2.

Panel A



Panel B



Internet Appendix

Appendix A

A.1 Economy Sample

For a sample of economies over the months July 1989 to June 2024, this paper examines how international trade and imperfect competition shape global equity risk premia. Following Della Corte, Riddiough, and Sarno (2016), I use a sample of 55 economies for developed and other markets: Argentina, Australia, Austria, Belgium, Brazil, Canada, Chile, China, Colombia, Croatia, Czech Republic, Denmark, Egypt, Estonia, Finland, France, Germany, Greece, Hong Kong, Hungary, Iceland, India, Indonesia, Ireland, Israel, Italy, Japan, Kazakhstan, Latvia, Lithuania, Malaysia, Mexico, Morocco, Netherlands, New Zealand, Norway, Philippines, Poland, Portugal, Russia, Singapore, Slovakia, Slovenia, South Africa, South Korea, Spain, Sweden, Switzerland, Thailand, Tunisia, Turkey, Ukraine, the United Kingdom, the United States, and Venezuela. The sample of developed markets is limited to stocks from the following 24 economies: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Hong Kong, Ireland, Israel, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, United Kingdom, and the United States. The variable descriptions and data sources are presented in Table A.1.

A.2 Economy-Level Summary Statistics

For this paper's final sample of stocks, Table A.2 reports the economy-level averages for stock returns where *Excess return* is the monthly return (in US dollars) to buying the stock at time $t - 1$ and then selling it at time t, in excess of the risk-free rate (taken from Kenneth French's Data Library). The table also shows the average for *Market value of equity* in each economy for the sample period, along with the average global single-sorted SIZE and IAROE portfolios in each

economy during the sample period. Finally, the table presents the average global single-sorted TECH and TDPRT portfolios in each economy during the sample period, and the average global single-sorted CRX portfolios in each economy during the sample period.

A.3 Test Assets

This section describes the construction and characteristics of the test portfolios used in the cross-sectional asset pricing tests.

A.3.1. *Test Portfolio Design*

The primary test assets consist of economy-industry portfolios formed from independent double sorts on economy and industry. This design offers several advantages for testing international asset pricing models. First, economy-industry portfolios align with the paper's theoretical framework, which emphasizes competitive displacement within industries across economies. Firms compete internationally within their industries rather than across unrelated sectors, making these portfolios natural test assets for displacement risk. Second, independent sorting on economy and industry ensures that test portfolios are not sorted on the characteristics that define the factors (firm size, relative profitability, or currency exposure), avoiding the spurious correlations documented by Lewellen, Nagel, and Shanken (2010) when test assets mechanically track factor construction.

For a robustness check, I construct an alternative set of test assets using economy-size double sorts using a selection process similar to that for economy-industry portfolios (see Section A.3.3). These portfolios are formed by independently sorting stocks on economy and firm size (market capitalization), following standard practice in the international asset pricing literature.

A.3.2. *The Economy-Industry Portfolios*

In this paper, I investigate economy-industry portfolios for (i) developed and other markets and (ii) developed markets only.

The first sample of test assets includes 20 economy-industry portfolios spanning both developed economies and other markets (emerging and frontier markets) with a sample period of May 1991 to June 2024, providing 398 monthly observations. In Table A.3, Panel A shows the portfolios represent diverse competitive environments across different development stages. Examples include Argentina–Food & Kindred Products (SIC 20), Brazil–Insurance Brokers & Services (SIC 64), Korea–Building Construction (SIC 15), Indonesia–Chemicals & Allied Products (SIC 28), and Poland–Apparel & Finished Products (SIC 23). Developed economies in this sample include Denmark–Chemicals (SIC 28), Japan–Metal Mining (SIC 10), United Kingdom–Oil & Gas Extraction (SIC 13), and Hong Kong–Electronic Equipment (SIC 36). The broader geographic coverage provides comprehensive tests of the asset pricing model across diverse competitive environments.

The second sample of test assets consists of 20 economy-industry portfolios restricted to developed economies with a sample period of July 1989 to June 2024, providing 420 monthly observations. Panel B of Table A.3 shows the representative portfolios include Switzerland–Industrial Machinery & Computer Equipment (SIC 35), Denmark–Chemicals & Allied Products (SIC 28), Finland–Paper & Allied Products (SIC 26), Norway–Oil & Gas Extraction (SIC 13), Hong Kong–Building Construction (SIC 15), Israel–Chemicals (SIC 28), and Japan–Agricultural Services (SIC 07). This sample serves two purposes: (a) robustness verification that the main results are not driven by emerging markets, and (b) benchmarking against models designed specifically for segmented markets (i.e., the world Fama-French five-factor model).

A.3.3. *Portfolio Selection Method*

This paper's portfolio selection follows a multi-stage process designed to ensure adequate portfolio observations, geographic diversification, industry balance, and statistical informativeness. The

choice of exactly 20 portfolios is guided by econometric considerations for conditional GMM estimation. With $T = 420$ monthly observations, $K = 4$ factors, and $J = 3$ conditioning instruments, the resulting 80 moment conditions ($N \times (J + 1) = 20 \times 4$) yield a moment-to-observation ratio of 0.19, consistent with the practical guideline of maintaining this ratio between 0.15 and 0.25 to ensure stable two-step GMM estimation (Ferson and Foerster, 1994). This choice aligns with standard practice in conditional asset pricing: Lettau and Ludvigson (2001) and Hodrick and Zhang (2001) use 25 portfolios with fewer conditioning instruments, while Nagel and Singleton (2011) use 5 to 10 portfolios when the conditioning set is more extensive. In implementing the selection process, I consider the following stages:

In Stage 1, I screen all candidate portfolios for extreme return variation. For each portfolio, I compute the 90% range, defined as the difference between the 95th and 5th percentiles of monthly excess returns. This tail-robust measure excludes extreme outliers while capturing the bulk of return dispersion. Portfolios with a 90% range exceeding 40 percentage points are excluded to avoid erratic return patterns that could distort cross-sectional tests. This conservative threshold ensures the selected portfolios exhibit reasonable return dispersion relative to the monthly frequency of the data.

Stage 2 employs a greedy forward selection algorithm that balances three objectives: maximizing complete observations (months where all selected portfolios have data), ensuring broad geographic representation, and maintaining balanced representation across competitive environments. To prevent any single country from dominating the cross-section, I enforce a maximum of 2 portfolios per economy. Industries are first classified into five groups based on quintiles of within-industry profitability dispersion. The selection process maintains a tight balance across these five industry groups using a round-robin strategy.

In Stage 3, I follow Lewellen, Nagel, and Shanken (2010) by computing leverage scores to identify the most informative portfolios for cross-sectional pricing tests. Leverage measures how unusual a portfolio's factor exposures are relative to the full cross-section. Portfolios with higher leverage provide more independent variation in the exposure space and thus contribute more information to the identification of risk premia. To obtain the final test asset set, I select the 20 portfolios with the highest leverage scores, subject to maintaining adequate geographic and industry diversity. The algorithm retains portfolios in order of decreasing leverage (starting with the most informative) until exactly 20 portfolios are selected, subject to two hard constraints: (a) at least 15 economies must remain represented, and (b) no industry profitability dispersion group may fall below 3 portfolios.

This multi-stage process ensures that the final 20 portfolios provide diverse representation across competitive environments and geographies while maximizing the statistical information content for cross-sectional pricing tests.

Table A.1. Descriptions and Sources

Panel A of this table presents the descriptions and sources of the variables used in this paper's empirical exercise. Panel B shows the descriptions of the model parameters, and the macroeconomic characteristics used for this paper's model simulations. Panel C presents the descriptions of the equity return parameters estimated in this paper, along with the model outcomes used as regressors for regression analysis.

Panel A: Variables

Variable	Description
Excess return	The monthly return (in US dollars) to buying the stock at time $t - 1$ and then selling it at time t, in excess of the risk-free rate. [Sources: Datastream; Kenneth French Data Library]
Market value of equity	The total market capitalization of a firm's equity (in June 2024 US dollars). [Sources: Datastream; International Monetary Fund]
Value-weighted excess return	The weighted mean of *Excess return* for a portfolio where the weight of each stock is its *Market value of equity*. [Sources: Datastream; Kenneth French Data Library; International Monetary Fund]
Total number of firms	The total number of unique firms in an economy. [Source: Datastream]
Number of firms	The number of active firms in a portfolio. [Source: Datastream]
Global market factor (GMKT)	The monthly return (in US dollars) of the global Morgan Stanley Capital International (MSCI) index (World IMI Total Return Index from July 1989 to December 1994; and ACWI IMI Total Return Index from January 1995 to June 2024) in excess of the risk-free rate. [Sources: Datastream; Kenneth French Data Library]
Global market factor EW (GMKTEW)	The monthly return (in US dollars) of the equal-weighted global Morgan Stanley Capital International (MSCI) index (World IMI Equal-Weighted Total Return Index from July 1989 to June 2024) in excess of the risk-free rate. [Sources: Datastream; Kenneth French Data Library]
Local market factor (LMKT)	The weighted mean of *Excess return* for all firms in an economy where the weight of each stock is its *Market value of equity*. [Sources: Datastream; Kenneth French Data Library]
Industry-adjusted return on equity	The residual from a regression of return on equity (net income divided by total equity) on (two-digit standard industry classification, SIC, code) industry fixed effects for all firms using the full data extraction period (January 1975 to March 2025). [Source: Datastream]
Industry profitability dispersion	The interquartile range of return on equity (net income divided by total equity) within each industry (two-digit standard industry classification, SIC, code). [Source: Datastream]
Technology	A measure of absolute advantage proxied by current gross domestic product (in US dollars). [Source: World Development Indicators (WDI), World Bank]
Trade protection	A measure of trade protection proxied by the (interpolated) weighted average of the import tariff rate across all products in an economy. [Source: World Development Indicators (WDI), World Bank]
Mean currency excess return	The annual average of the currency excess return in an economy, where the currency excess return is computed as the monthly return (in US dollars) to buying a foreign currency in the forward market (at the forward rate) at time $t - 1$ and then selling it in the spot market (at the spot rate) at time t. [Source: Datastream]

Panel B: Model Parameters and Economic Characteristics

Parameter	Description
β_p	The average labor share in gross manufacturing production. [Source (Estimate): Eaton and Kortum (2002)]
α	Manufacturing income as a percentage of labor income. [Source (Estimate): Eaton and Kortum (2002)]
θ	The prevalence of comparative advantage. [Source (Estimate): Eaton and Kortum (2002)]
κ	The scaling factor for all economic shocks, proxied by the economy (cross-sectional) average of the (time-series) annual standard deviation of economic growth. [Source (Data): World Development Indicators (WDI), World Bank]
$\rho_{\eta\nu}$	The correlation between heterogeneous global shocks and homogeneous global shocks, a moment proxied by the maximum reasonable correlation between sectoral shocks and common shocks. [Source (Estimate): De Graeve and Schneider (2023)]
Characteristic	**Description**
$c_{i,1}$	The input cost in economy i at time t = 1, which is a function wages, prices and the average labor share in gross manufacturing production. Wage and labor share estimates are taken from Eaton and Kortum (2002), while price data are taken from the Penn World Tables (PWT). [Source (Estimate): Eaton and Kortum (2002); Source (Data): Penn World Tables 9.1]
$\ln(Y_{i,1})$	The log of the total income in economy i at time t = 1, represented by local-currency gross domestic product (GDP) in 1990 converted to US dollars using the exchange rate in 1990. [Source (Data): World Development Indicators (WDI), World Bank]
$\ln(T_i)$	The log of the state of technology (a measure of absolute advantage) in economy i. [Source (Estimate): Eaton and Kortum (2002)]
$\ln(d_n)$	The log of the average import openness in economy n using destination estimates from Eaton and Kortum (2002) adjusted for the effect of the median distance bin. $\ln(d_n)$ is used a scale parameter along with a shape parameter of 2 in a beta distribution to simulate bilateral log geographic barriers $\ln(d_{ni})$. Bilateral geographic barriers always satisfy the triangle inequality of cross-border arbitrage. [Source (Estimate): Eaton and Kortum (2002)]

Panel C: Equity Return Parameters and Outcomes for Simulated Firms

Equity Return Parameter	Description
ϱ	The degree of price stickiness in the global economy.
ω_S	The relative importance of supply shocks in the global economy.
ω_D	The relative importance of demand shocks in the global economy.
δ	The global ratio of dividends to operating income.
Outcome	**Description**
$2\sum_{n\in\Lambda_{ki,1}} x_{kn,1}$	The total revenue of the firm at time t = 1 multiplied by 2 (i.e., the historical average of the equity-to-sales ratio).
$pm_{ki,1}$	The firm's operating income at time t = 1, divided by $2\sum_{n\in\Lambda_{ki,1}} x_{kn,1}$.
Industry concentration	The total number of firms that produce a good *j* at time t = 1.
CRX Portfolio	The portfolio number based on the quintile of excess currency returns at time t = 2.

Table A.2. Stock Characteristics at the Economy Level

This table presents a summary of stock characteristics at the economy level. The sample period is from July 1989 to June 2024. *Total number of firms* is the total number of unique firms in an economy. *Number of firms* is the number of active firms in a portfolio. *Market value of equity* is the total market capitalization of a firm's equity (in June 2024 US dollars). *Excess return* is the monthly return (in US dollars) to buying the stock at time $t - 1$ and then selling it at time t, in excess of the risk-free rate. *Value-weighted excess return* is the weighted mean of *Excess return* for a portfolio where the weight of each stock is its *Market value of equity*. Single-sorted portfolios are created in June of year y for the evaluation of monthly returns from July of year y to June of year $y + 1$. Five portfolios are created based on quintiles for each sorting characteristic (*Market value of equity*, SIZE; *Industry-adjusted return on equity*, IAROE; *Technology*, TECH; *Trade protection*, TDPRT; *Industry profitability dispersion*, IDISP; and *Mean currency excess return*, CRX). *Industry-adjusted return on equity* is the residual from a regression of return on equity (net income divided by total equity) on (two-digit standard industry classification, SIC, code) industry fixed effects for all firms using the full data extraction period (January 1975 to March 2025). *Technology* is a measure of absolute advantage proxied by current gross domestic product (in US dollars). *Trade protection* is a measure of trade protection proxied by the (interpolated) weighted average of the import tariff rate across all products in an economy. *Industry profitability dispersion* is the interquartile range for return on equity within an industry. *Mean currency excess return* is the annual average of the currency excess return in an economy, where the currency excess return is computed as the monthly return (in US dollars) to buying a foreign currency in the forward market (at the forward rate) at time $t - 1$ and then selling it in the spot market (at the spot rate) at time t. For TECH, TDPRT, IDISP and CRX, single-sorted portfolios for portfolio year y are based on the year $y - 1$ value for the characteristic of the economy where the firm is listed. These single-sorted portfolios are used to construct factors as Q5 – Q1 long-short factor mimicking portfolios. Single-sorted portfolios for SIZE and IAROE are created in June of year y for summary statistics (using *Market value of equity* in June of year y and *Industry-adjusted return on equity* in December of year $y - 1$). Variable descriptions are presented in Table A.1.

		Variable Mean			Average Single-Sorted Portfolio Mean				
Economy	Total number of firms	Market value of equity	Excess return (EW)	Excess return (VW)	SIZE	IAROE	TECH	TDPRT	CRX
Argentina	136	1546.89	0.36	1.47	2.65	2.83	3.43	4.61	3.63
Australia	2488	794.54	−0.10	0.62	2.67	2.91	4.00	2.91	2.94
Austria	278	843.35	−0.02	0.64	2.83	2.73	3.40	1.94	2.64
Belgium	403	1369.55	−0.01	0.53	2.80	3.02	3.63	1.26	3.36
Brazil	719	2990.73	0.49	1.17	3.24	3.04	4.63	4.79	3.30
Canada	3110	887.21	0.06	0.75	2.81	3.09	4.97	1.47	2.66
Switzerland	476	3961.16	0.21	0.74	3.72	3.02	4.00	2.00	2.86
Chile	178	1014.03	0.31	0.63	3.20	3.00	1.89	3.06	2.95
China	5266	2019.97	−0.01	0.82	4.40	3.36	4.91	4.55	2.71
Colombia	72	1914.25	0.02	0.66	3.56	2.98	2.11	4.41	2.89
Czech Republic	275	242.89	−0.05	0.86	1.85	2.80	1.85	1.78	2.85
Germany	1542	1826.92	0.01	0.72	2.74	3.00	5.00	1.26	2.91
Denmark	444	976.54	0.10	0.99	2.67	2.89	2.86	1.26	2.74
Egypt	214	366.54	−0.56	0.51	2.56	3.19	1.94	5.00	3.94
Spain	95	309.90	−0.24	0.06	2.48	2.83	4.63	1.26	3.00
Estonia	46	312.93	0.35	0.77	2.46	2.80	1.00	1.14	2.71
Finland	337	1096.29	0.10	0.78	3.16	3.14	2.63	1.57	2.33
France	2515	1515.56	0.10	0.69	2.70	3.07	5.00	1.26	3.36
United Kingdom	5458	1152.42	−0.22	0.45	2.70	3.06	5.00	1.26	2.77
Greece	439	388.87	0.42	1.18	2.53	2.79	2.63	1.26	2.60
Hong Kong	1152	2746.70	−0.17	1.05	3.55	2.98	2.57	1.00	2.60
Croatia	257	244.33	1.10	2.06	1.92	2.42	1.00	1.55	2.84
Hungary	116	385.28	−0.02	1.16	2.08	2.97	1.37	2.03	3.08
Indonesia	95	881.54	−0.48	0.20	2.80	3.14	3.57	3.74	3.36
India	2247	28.13	0.15	1.35	1.33	2.95	4.40	5.00	2.96
Ireland	112	1129.20	0.02	0.68	3.12	3.21	2.34	1.26	3.17
Iceland	10	1670.32	0.82	0.79	4.17	3.04	1.00	2.10	3.21
Israel	994	266.24	0.31	1.13	2.29	2.90	2.54	2.70	2.79

		Variable Mean			Average Single-Sorted Portfolio Mean				
Economy	Total number of firms	Market value of equity	Excess return (EW)	Excess return (VW)	SIZE	IAROE	TECH	TDPRT	CRX
Italy	896	1628.46	−0.16	0.41	3.19	2.98	5.00	1.26	3.18
Japan	6010	1353.38	0.07	0.55	3.25	2.95	5.00	3.11	2.63
Kazakhstan	80	419.78	−0.10	3.87	2.63	3.22	1.36	3.42	3.05
Korea	3862	501.71	0.42	1.52	2.62	2.96	4.29	4.29	2.83
Lithuania	56	270.80	0.17	0.49	2.61	2.79	1.00	1.14	2.64
Latvia	39	54.42	0.09	0.62	1.72	2.80	1.00	1.37	3.00
Morocco	118	703.78	0.43	0.70	3.04	3.23	1.00	4.79	3.47
Mexico	262	2026.15	0.05	0.88	3.73	2.90	4.29	3.38	3.30
Malaysia	643	739.17	−0.17	0.37	2.90	2.79	2.17	3.74	2.82
Netherlands	458	3080.63	−0.01	0.72	3.14	3.31	4.00	1.26	2.82
Norway	751	673.04	−0.04	0.81	2.98	2.81	3.14	2.74	2.54
New Zealand	238	580.70	−0.11	0.35	2.99	2.93	1.86	2.42	3.23
Philippines	81	1680.57	0.31	0.99	3.49	3.06	2.11	3.43	2.74
Poland	1029	251.28	0.76	1.57	1.99	3.12	3.27	1.72	3.19
Portugal	218	734.23	−0.02	0.43	2.68	2.87	2.54	1.26	3.00
Russian Federation	238	3443.71	1.25	2.21	3.29	3.31	4.40	4.48	3.16
Singapore	379	1399.53	−0.10	0.56	3.47	3.01	2.26	1.00	2.80
Slovak Republic	109	62.79	1.12	1.02	1.41	2.55	1.00	1.43	3.71
Slovenia	110	205.43	0.46	0.81	2.21	2.44	1.00	1.54	2.67
Sweden	1423	666.36	−0.13	0.84	2.65	2.99	3.94	1.26	2.60
Thailand	423	1085.30	−0.25	0.48	2.94	3.00	2.94	4.50	3.00
Tunisia	84	136.16	0.49	0.97	2.39	2.93	1.00	4.93	2.95
Türkiye	521	539.49	0.69	2.34	2.69	3.29	3.71	2.80	3.19
Ukraine	177	224.12	−0.39	0.28	2.19	2.66	1.51	3.14	3.74
United States	16365	2716.77	0.24	0.96	3.54	2.92	5.00	1.56	.
Venezuela	22	178.65	−0.24	−0.31	1.79	2.69	2.33	4.81	4.00
South Africa	674	940.66	−0.12	0.81	2.94	3.46	2.97	4.09	2.47

Table A.3. Economy-Industry Portfolio Test Assets

This table presents the summary statistics for the 20 economy-industry portfolio test assets using developed and other markets (Panel A) and developed markets only (Panel B). For developed and other markets, the sample period is from May 1991 to June 2024. For developed markets only, the sample period is from July 1989 to June 2024. The variable definitions [descriptions] are presented in Table 3 [Table A.1].

Panel A: Developed and Other Markets

		Variable mean			Average single-sorted portfolio mean		
Economy	**SIC**	**Total number of firms**	**Market value of equity**	**Excess return (EW)**	**Excess return (VW)**	**SIZE**	**IAROE**	**IDISP**
Argentina	20	8	234.72	0.43	0.88	2.66	2.26	2.15
Brazil	64	6	4796.84	0.10	0.39	4.22	3.43	4.32
Denmark	28	16	6411.64	0.62	1.56	3.42	3.41	3.88
Finland	26	8	3690.80	0.34	0.65	4.08	2.72	1.71
United Kingdom	13	129	3235.49	−0.41	0.41	2.84	3.10	4.29
Greece	20	21	157.82	0.16	0.64	2.30	2.37	2.15
Hong Kong	36	55	1939.58	0.02	1.31	3.43	3.21	3.62
Indonesia	28	9	116.46	−0.25	−0.01	2.11	4.05	3.88
India	29	7	531.00	0.45	0.57	2.73	2.94	3.00
Israel	27	5	24.66	0.44	0.61	1.54	3.08	2.88
Israel	28	27	1730.30	0.26	1.23	2.76	2.90	3.88
Japan	07	4	1298.72	0.28	0.16	2.78	2.89	2.97
Japan	10	5	1449.10	−0.18	0.09	3.77	4.29	4.79
Korea	15	68	418.96	0.40	1.09	2.73	2.87	2.32
Korea	20	104	370.17	0.99	1.80	2.95	2.54	2.15
Mexico	60	16	3237.52	−0.16	0.32	4.44	3.00	1.06
Malaysia	65	55	232.04	−0.37	0.01	2.61	2.96	1.71
Poland	23	9	41.32	0.41	0.83	1.77	2.18	2.91
Portugal	16	7	399.26	0.11	0.34	3.44	2.94	1.56
Sweden	13	8	200.43	0.21	0.72	2.64	3.20	4.29

Panel B: Developed Markets Only

			Variable mean			Average single-sorted portfolio mean		
Economy	**SIC**	**Total number of firms**	**Market value of equity**	**Excess return (EW)**	**Excess return (VW)**	**SIZE**	**IAROE**	**IDISP**
Australia	01	12	191.82	−0.12	0.35	2.38	2.16	1.81
Belgium	20	11	11619.61	0.35	0.53	3.36	2.61	2.19
Switzerland	35	36	2368.96	0.48	0.97	3.89	3.08	2.78
Germany	01	5	364.25	0.25	0.72	2.36	2.14	1.81
Denmark	28	16	6167.42	0.59	1.47	3.40	3.37	3.83
Finland	26	8	3602.65	0.18	0.54	4.06	2.53	1.75
United Kingdom	13	129	3204.44	−0.43	0.44	2.84	3.10	4.17
Greece	20	21	158.98	0.59	1.22	2.31	2.30	2.19
Greece	28	13	269.39	0.44	1.14	2.83	2.95	3.83
Hong Kong	15	97	3515.79	−0.05	1.01	3.85	2.93	2.36
Hong Kong	36	55	1936.55	0.19	1.44	3.43	3.21	3.56
Ireland	13	5	823.16	−0.09	0.55	2.98	3.25	4.17
Israel	27	5	25.47	0.48	0.56	1.54	3.08	2.92
Israel	28	27	1724.55	0.21	1.11	2.76	2.90	3.83
Italy	16	16	317.93	−0.01	0.38	2.95	3.21	1.53
Japan	07	4	1312.36	0.25	0.14	2.78	2.87	3.08
Japan	10	5	1472.08	−0.11	0.16	3.79	4.26	4.81
Norway	13	83	762.66	0.12	1.00	3.35	2.83	4.17
Norway	15	11	345.90	−0.24	0.36	2.89	2.82	2.36
Portugal	27	5	238.64	−0.24	−0.07	2.75	1.90	2.92

Appendix B

B.1 A Toy Example: Displacement and the Failure of Single-Factor Models

To understand the intuition for this paper's model, I develop a stylized toy example that simplifies along three dimensions to enable accessibility. First, the supply-side competition structure uses a simple Gaussian contest function rather than Ricardian trade with Bertrand competition in general equilibrium. Second, the toy example uses i.i.d. random draws for competitive outcomes rather than the paper's full set of structured supply-side and demand-side shocks with specified correlation patterns. Third, the paper's model determines market returns endogenously within a system driven by economic shocks affecting all results, while the toy example treats the market return as independent and exogenous for the analysis of risk premia (Sections B.1.4 and B.1.5). The example features three economies (US, Japan, South Africa), two industries (Technology and Materials), and one firm per economy-industry pair, resulting in six firms total. Each industry comprises $Mkt = 20$ discrete markets in each period, with market size $Msize_t$ representing aggregate demand.

The toy example emphasizes a crucial feature of this paper's model: *more productive firms win more markets on average, but with period-to-period variation*. This captures the essential economics of competitive displacement where firms with greater productivity tend to have larger market shares. However, no firm's position is deterministic because competitive outcomes fluctuate due to supply-side shocks. Within each industry, firms compete for markets based on their productivity. Firm i has fixed productivity $prod_i > 0$, which can be interpreted as its fundamental cost advantage. Markets are allocated through a contest success function that captures stochastic competition with Gaussian costs where $cq > 0$ is a contest intensity parameter.

[B1] $$share_i(cq) = \frac{e^{cq \ln prod_i}}{\sum_j e^{cq \ln prod_j}} = \frac{prod_i^{cq}}{\sum_j prod_j^{cq}}$$

$share_i$ represents firm i 's probability of winning any given market. A more productive firm has a greater $share_i(cq)$ and wins more markets on average. The actual number of markets captured in period t follows a multinomial distribution: $mc_{it} \sim Multinomial\big(Mkt, share_i(cq)\big)$. This structure parallels probabilistic competition in EK and BEJK where random draws determine the costs for each good and the lowest-cost supplier wins. It is also consistent with the endogenous reallocation toward more productive firms in Melitz (2003), where fixed operating and exporting costs create productivity cutoffs that determine market participation. [i]

In this simple framework, profit equals sales, which in turn equals the number of markets captured times market size: $Sales_{it} = mc_{it} \times Msize_t$. Firm returns are then:

[B2] $$Ret_i = \frac{mc_{i2}Msize_2 - mc_{i1}Msize_1}{mc_{i1}Msize_1}$$

The global market portfolio is the value-weighted portfolio of all six firms, with weights fixed at values at t = 1, and the risk-free rate is zero.

There are two distinct shock types: supply-side shocks and demand-side shocks. Demand-side shocks change $Msize_t$ while holding market allocations fixed. Supply-side shocks represent new random competitive realizations: each industry redraws its markets from the same multinomial distribution (with unchanged $prod_i$ and cq). This captures the idea that competitive outcomes vary over time. Although shocks typically operate at multiple levels affecting both relative productivities and market outcomes, the toy example presented here captures the essential

[i] In EK, countries draw idiosyncratic good-level productivities from a Fréchet distribution, and each good is supplied by the lowest-cost country; more productive locations therefore supply more goods in expectation, even though any individual good's assignment is stochastic. BEJK apply the same mechanism at the plant level, implying that highly productive plants have a higher probability of serving each destination and thus export to more markets on average, while low-productivity plants face a nontrivial chance of serving none. Melitz (2003) introduces fixed operating and exporting costs that generate productivity cutoffs, leading market share to be endogenously reallocated toward more productive firms and making firms near the cutoff highly sensitive to shocks. Across these frameworks, the unifying implication is that productivity governs expected market reach, with the realized set of markets served determined by stochastic draws (EK/BEJK) or endogenous selection margins (Melitz). In this paper, the core idea is that more productive firms win more markets on average, but competitive outcomes vary period-to-period.

competitive selection mechanism in reduced form: I hold productivities fixed and let random market allocations represent the combined effect of these various shocks.

Suppose the US technology firm is highly productive, the Japanese technology firm has moderate productivity, and the South African technology firm is the least competitive. In materials, the pattern differs: the Japanese firm is the strongest, the US firm is moderate, and the South African firm trails. At t = 1, I set productivities to generate the intended heterogeneity. Technology has $prod_{US,T} = 4.5$, $prod_{JP,T} = 1.0$, $prod_{ZA,T} = 0.5$; Materials has $prod_{US,M} = 2.4$, $prod_{JP,M} = 1.6$, $prod_{ZA,M} = 1.0$. With contest intensity cq = 1, shares are proportional to productivity. The US technology firm captures 15 markets, the Japanese firm captures 3 markets, and the South African firm captures 2 markets for sales of 750, 150, and 100 respectively, yielding market weights of 37.5%, 7.5%, and 5%. The US materials firm captures 10 markets, the Japanese firm captures 6 markets, and the South African firm captures 4 markets for sales of 500, 300, and 200 respectively, delivering market weights of 25%, 15%, and 10%. Here $Msize_1 = 50$ and total global sales equal 2000. First-period weights remain fixed when computing second-period market returns.

At t = 2, there are demand-side shocks that change the overall size of the market and supply-side shocks that reallocate market share across competitors. Crucially, supply-side shocks (i.e., realized market allocations from multinomial draws) don't change the aggregate pie, but they redistribute who gets what share. Consider scenarios that reveal the roles of these shocks in competitive displacement and the contamination of single-factor SDF proxy (i.e., the global market portfolio).

Under pure demand-side expansion with market allocations unchanged, the global market size increases by 15% to $Msize_2 = 57.5$. Here the global economy booms while competitive positions remain frozen. All firms' sales scale proportionally: The US technology firm earns 862.5

(15 × 57.5), the Japanese technology firm earns 172.5 (3 × 57.5), and so forth. All six firms earn identical returns of 15%. The value-weighted market return is 15%, and every firm exhibits a global market portfolio exposure (or alignment ratio) of one ($Ret_{i2}/Ret_{G2} = 1$). A similar finding occurs if the global market size decreases by 15% to $Msize_2 = 42.5$ and a value-weighted market return of –15%: $Ret_{i2}/Ret_{G2} = 1$. Conditional on all firms having the same exposure to aggregate demand shocks, these outcomes are consistent with the "textbook case" without contamination where a positive exposure explains returns.

What happens when the market size stays fixed, but competitive outcomes shift? Under pure supply-side market reallocations with market size unchanged ($Msize_2 = Msize_1 = 50$), a random draw gives the following new market allocations for technology firms: the US firm now has 16 up from 15, the Japanese firm has 3, and the South African firm has 1 down from 2. For materials firms: the US firm now has 11 up from 10, the Japanese firm has 5 down from 6, and the South African firm has 4. Although the aggregate pie remains unchanged with total global sales at 2000, the sales are reallocated across firms. While there is no change in the global market portfolio value, there is substantial variation in equity returns from –50% to 10%. This outcome isolates competitive displacement risk, which is orthogonal to the global market portfolio returns. A single-factor model like the world CAPM cannot explain this outcome since aggregate demand is unchanged (i.e., the market size remains constant) yet individual firm returns vary substantially.

B.1.1. *Expansion and Displacement*

Under the complete specification with supply-side shocks and a demand-side expansion, the global market size increases by 15% to $Msize_2 = 57.5$. How do supply and demand interact with the same random draw of market allocation as before? For the technology sector, the US firm's sales equal 920 with an equity return of 22.67%, the Japanese firm experiences sales of 172.5 with an

equity return of 15%, and the South African firm's sales decline to 57.5 for an equity return of –42.5%. For the materials sector, the US firm experiences sales of 632.5 with an equity return of 26.5%, the Japanese firm's sales equal to 287.5 with an equity return of –4.17%, and the South African firm's sales increase to 230 for an equity return of 15%. The global market portfolio return is 15%, but the exposures now range from −2.83 to 1.77. Here's the striking pattern: The vulnerable South African technology firm loses 42.5% in a booming market, an obvious deviation from the predictions of the world CAPM. The South African technology firm captures one fewer market as the market size increases. This multiplicative interaction of (1/2) × (57.5/50) produces a large negative exposure despite the positive aggregate demand shock. Here the operating leverage mechanism makes vulnerable firms especially sensitive to competitive displacement. The South African technology firm starts with just 2 markets, and losing one market means losing 50% of its capacity. When this 50% capacity loss occurs during a boom, the multiplicative effect still produces a huge loss.

B.1.2. *Contraction and Displacement*

Under the complete specification with supply-side shocks and a demand-side contraction, the global market size contracts by 15% to $Msize_2 = 42.5$. Under a value-weighted market return of –15%, sales for the US technology firm decline to 680 with an equity return of –9.33%, the Japanese technology firm experiences sales of 127.5 with an equity return of –15%, and the South African technology firm's sales decline to 42.5 for an equity return of –57.5%. For the materials sector, the US firm experiences sales of 467.5 with an equity return of –6.5%, the Japanese firm's sales equal to 212.5 with an equity return of –29.17%, and the South African firm's sales decrease to 170 for an equity return of –15%. The vulnerable South African technology firm loses 57.5% due to both losing a market and facing a shrinking market size: (1/2) × (42.5/50) = 0.425.

Moreover, between expansions and contractions, the same market reallocation in the technology sector (the US firm has 16 up from 15, and the South African firm has 1 down from 2) produces different outcomes. The vulnerable South African technology firm exhibits an alignment ratio of –2.83 in expansions but 3.83 in contractions—larger in absolute terms during downturns due to multiplicative effects compounding differently.

To illustrate the range of possible outcomes, consider an alternative draw for market allocations under a value-weighted market return of –15%. For technology firms: the US firm has 17 up from 15, the Japanese firm has 3, and the South African firm has zero markets (i.e., complete displacement) down from 2. For materials firms: the US firm has 8 down from 10, the Japanese firm has 6, and the South African firm has 6 up from 4.

This alternative realization reveals two critical features. First, complete displacement: The vulnerable South African technology firm falls to zero markets and suffers a −100% return. In general, the probability of complete displacement, $Pr[mc_{it} = 0] = \left(1 - share_i(cq)\right)^{Mkt} \approx 19\%$ for this South African technology firm with expected share of 0.083 for 20 markets. The threat of complete displacement creates severe left-tail risk for vulnerable firms. Second, negative exposure: The South African materials firm gains two markets despite the contraction in aggregate demand, earning a return of 27.5% while the market falls −15%. The negative alignment ratio ($Ret_{i2}/Ret_{G2} = -1.83$) shows that market reallocation can even dominate contraction in aggregate demand, a possibility ruled out in a traditional single-factor model.

B.1.3. *Displacement and the Asymmetry of Equity Returns*

When costs are allowed to change from time t = 1 to time t = 2, imperfect competition introduces the possibility of asymmetric outcomes. For example, firm-level and economy level shocks that "average out" in [10] and [11] can have a disproportionate impact on profits and returns for

vulnerable firms with thin margins of competition. These firms are particularly vulnerable to complete displacement with –100% returns when operating in few or even a single destination market.

To characterize the asymmetric return distributions arising from competitive displacement in the toy example, I isolate supply-side effects by holding market size constant ($Msize_2 = Msize_1 = 50$). In this specification, returns depend entirely on changes in markets captured: $Ret_i = (mc_{i2} - mc_{i1})/mc_{i1}$. Within each industry, the market allocation follows a multinomial distribution, $mc_{it} \sim Multinomial\big(Mkt, share_i(cq)\big)$. For analytical tractability, I characterize each firm's marginal distribution: $mc_{it} \sim Binomial\big(Mkt, share_i(cq)\big)$ with probability mass function:[ii]

[B3] $$Pr[mc_{it} = k] = \binom{Mkt}{k} share_i(cq)^k \big(1 - share_i(cq)\big)^{Mkt-k}$$

For firm i with mc_{i1} starting markets and $share_i(cq)$ success probability, the expected return is $E[Ret_i] = (E[mc_{i2}] - mc_{i1})/mc_{i1} = (Mkt \times share_i(cq) - mc_{i1})/mc_{i1}$, and the return variance is $Var(Ret_i) = \Big(Mkt \times share_i(cq) \times \big(1 - share_i(cq)\big)\Big)/{mc_{i1}}^2$. With $\mu_i = E[Ret_i]$ and $\sigma_i = \sqrt{Var(Ret_i)}$, the standardized third moment (or skewness) is:

[B4] $$\frac{E\big[(Ret_i - \mu_i)^3\big]}{\sigma_i^3} = \frac{\sum_{k=0}^{Mkt} Pr[mc_{it}=k] \times \left[\frac{k - mc_{i1}}{mc_{i1}} - \mu_i\right]^3}{\left[\sum_{k=0}^{Mkt} Pr[mc_{it}=k] \times \left[\frac{k - mc_{i1}}{mc_{i1}} - \mu_i\right]^2\right]^{3/2}}$$

To illustrate the asymmetric return distributions, I focus on the technology sector, which features a stark distinction between the dominant firm in the US and the vulnerable firm in South Africa. The South African firm starts with 2 markets ($share_i(cq) = 0.083$), and the US firm with

[ii] While the joint allocation is multinomial (markets won by one firm cannot be won by another), the marginal distribution for any single firm is binomial where each market is independently won by firm i with success probability $share_i(cq)$. This result permits a closed-form calculation of individual firm return distributions that preserves the competitive structure.

15 markets ($share_i(cq) = 0.75$). Panel A of Figure B.1 visualizes the return distributions, highlighting the contrast between the vulnerable South African firm and dominant US firm.

Since returns are equal to $(mc_{i2} - mc_{i1})/mc_{i1}$, the percentage impact of any market change is inversely proportional to starting position, an effect called hyperbolic scaling. On the left side, Panel A of Figure B.1 shows the South African firm faces a 19% probability of complete displacement, a 32% probability of losing one market, and declining probabilities for positive outcomes. The hyperbolic scaling amplifies each market change to ±50%, while its small $share_i(cq) = 0.083 < mc_{i1}/Mkt = 0.10$ implies a greater probability of losing markets than gaining them. The result is a pronounced negative skewness of returns: a 51% probability mass at –50% or worse, including the catastrophic –100% outcome, versus only a 7% probability above 100%. Put simply, the vulnerable firm faces coin-flip odds of losing 50% or more, including a roughly 1-in-5 chance of complete failure.

On the right side, Panel A of Figure B.1 shows the US firm's distribution centers tightly around the starting position of 15 markets, with a 20% probability of a 0% return (i.e., maintaining exactly 15 markets). Large losses below –20% have negligible probability (i.e., less than 1%), while the distribution extends to 33% with a 1% likelihood. The result is mild positive skewness where the right tail extends slightly further in percentage terms due to the unbounded upside. In stark contrast to the vulnerable firm, the dominant firm faces a tight, well-behaved distribution centered near zero. Hence large losses are extremely unlikely.

The contrast between the vulnerable firm and the dominant firm in Panel A of Figure B.1 suggests that competitive displacement creates a nonlinear risk on the supply side. At one end of the risk spectrum, the vulnerable South African firm exhibits a 19% probability of complete displacement, which requires a substantial risk premium. At the other end, the dominant US firm's

mild positive skew warrants a minimal risk premium. Return asymmetry concentrates among vulnerable firms on the supply side through three mechanisms: First, hyperbolic scaling where each unit market change represents ±50% returns for the 2-market vulnerable firm but only ±6.7% returns for the dominant 15-market firm. Second, imbalanced displacement probabilities where the vulnerable firm is more likely to lose markets than to gain them ($share_i(cq) < mc_{i1}/Mkt$). Third, vulnerable firms, with the threat of complete displacement, face a hard floor of –100% returns with no symmetric return ceiling.

B.1.4. *Demand-Side Heterogeneity and Equity Risk Premia*

The preceding analysis isolated displacement risk on the supply side by holding market size constant, thereby revealing asymmetries in return distributions. However, a complete characterization of equity risk premia within the toy example requires an acknowledgement of market exposure on the demand side.

Consider the case of [12] as a benchmark with only demand-side shocks. These demand-side shocks are noteworthy for engendering symmetry in the distribution of stock returns (see Section C.3). Likewise, deviations from the line of best fit (i.e., residuals) are distributed symmetrically. While the earlier treatment of the pure demand-side effect viewed every firm as having a uniform exposure to aggregate demand shocks, a more realistic characterization consists of firms with heterogeneous exposures. Therefore, to capture demand-side heterogeneity, I introduce a specification where larger, more productive firms have greater exposure to the global market portfolio. Note that this specification is simply consistent with the statistical fact that larger firms make up a greater portion of the value-weighted market return; I do not impose the assumption that vulnerable firms should have greater exposure to systematic risk.

To study equity risk premia, I focus on the materials sector because it provides a more

balanced competitive structure compared to the technology sector: The South African materials firm starts with 4 markets, the Japanese materials firm with 6 markets, and the US materials firm with 10 markets.

The specification for demand-side heterogeneity first standardizes the market exposure by imposing a beta of one for the firm with the average market share. Each firm's beta is therefore determined by the firm's deviation from the average market share.

[B5] $$Beta_i = 1 + \left(\frac{mc_{i1}}{Mkt} - \frac{\overline{mc_{i1}}}{Mkt}\right)$$

Under this specification, South African materials firm has a market beta of 0.867, the Japanese materials firm has a beta of 0.967, and the US materials firm has a beta of 1.167. I also assume that the annual world market return is normally distributed with a mean of 10% and a standard deviation of 15%. In the absence of idiosyncratic volatility, each firm's expected excess return and return volatility are derived as follows.

[B6] $$E[Ret_i] = Beta_i \times E[Ret_M]$$

$$\sigma_i = Beta_i \times \sigma_M$$

On the left side, Panel B of Figure B.1 shows the results for the three materials firms. The vulnerable South African firm exhibits the lowest beta and consequently the least volatility (13.0%). The dominant US firm shows the greatest volatility (17.5%). The figure depicts a positive linear relationship between market exposure and expected returns. Unlike the supply-side distributions in Panel A of Figure B.1, where volatilities ranged from 12.9% to 61.7% with severe asymmetries, demand-side volatilities span a modest 13.0% to 17.5% range. By construction, risk (i.e., volatility) scales linearly with beta. Hence demand-side returns exhibit no skewness and there is no tail risk from complete displacement.

B.1.5. *Weighting Supply and Demand to Derive Equity Risk Premia*

In Section B.1.3, competitive displacement on the supply side creates severe asymmetry where the vulnerable firm exhibits extreme volatility with pronounced negative skewness. The dominant firm, however, shows moderate volatility with mild positive skewness. In Section B.1.4, market exposure on the demand side operates so that volatility scales linearly from 13.0% to 17.5% across materials firms, with no skewness and symmetric distributions. The complete characterization of equity risk premia requires examining how displacement risk and market exposure combine when firms face simultaneous supply-side shocks and demand-side shocks. When both forces operate together, which risk dominates?

The toy example treats displacement risk on the supply side and market exposure on the demand side as independent components that can be combined through weighted averages. This independence assumption permits a transparent exploration of how relative weights determine equity risk premia, at the cost of abstracting away from correlated shocks and the interaction between displacement risk and market returns. For any weighting scheme, the combined return volatility for firm i equals:

[B7] $$\sigma_i^{combined} = \sqrt{wgt_{supply}^2 \times \left(\sigma_i^{supply}\right)^2 + wgt_{demand}^2 \times \left(\sigma_i^{demand}\right)^2}$$

Here I focus on return volatility rather than the expected (excess) return as the measure of the equity risk premium because the supply-side measure of expected returns does not reflect risk premia. In a Gaussian contest, the expected return is a measure that reverts toward equilibrium market shares. A firm currently holding fewer markets than its equilibrium share ($share_i(cq) > mc_{i1}/Mkt$) exhibits a positive expected return due to positional drift, and not because it requires compensation for risk. Return volatility, by contrast, captures the risk from hyperbolic scaling, imbalanced displacement probabilities, and the threat of complete displacement.

On the right side, Panel B of Figure B.1 presents combined volatilities for the three materials firms under a demand-dominated weighting scheme (25% supply, 75% demand) which correspond roughly to the demand-dominated weights used for this paper's model (i.e., weights derived from ω_D and ω_S): the South African firm at 14.8%, the Japanese firm at 13.9%, and US firm at 14.3%. The reason for the weight imbalance is that supply-side generates extreme volatilities, far exceeding observed equity return volatility. Observed equity returns exhibit substantially lower volatility, necessitating that demand-side shocks contribute the majority of return volatility.

However, even with these demand-dominated weights, the ordering of equity risk premia is influenced by the scale of the supply side. The extreme magnitude of supply-side displacement risk (44.7%) means that even at a smaller 25% weight, the demand-side pattern reverses. In comparison to the image on the left side of Panel B where the dominant US materials firm shows the greatest demand-side return volatility, the right side of Panel B shows that the vulnerable South African materials firm has the greatest combined return volatility.

When investigating the overall pattern of return volatility, a U-shape can emerge where vulnerable and dominant firms exhibit greater volatility compared to the middle firm. This U-shaped pattern may arise because different mechanisms dominate at the extremes. The vulnerable firm inherits high volatility from supply-side displacement risk, while the dominant firm inherits elevated volatility from demand-side market exposure. The middle firm has a balanced position from both sides, yielding the lowest combined return volatility.

This toy example demonstrates why single-factor models fail under competitive displacement. Vulnerable firms face two distinct risks: aggregate demand risk (captured by the market factor) and competitive displacement risk (orthogonal to the market). Consequently,

vulnerable firms exhibit severe tail risk because of the threat of complete displacement and can produce negative market exposures when market reallocation moves opposite to aggregate demand. At realistic relative weights where demand shocks dominate, equity risk premia exhibit a downward (possibly U-shaped) relation across market exposures. Hence the vulnerable firm with the lowest market exposure requires the greatest equity risk premium (14.8% volatility). In the CAPM, a low-beta firm should earn low returns because of a weaker exposure to systematic risk, but here, the vulnerable firm exhibits a low (or negative) market exposure because the market return is an outcome of competition. Instead of requiring a small equity risk premium, the vulnerable firm has a large equity risk premium because of displacement risk.

While deliberately stylized, this toy example reveals that competitive dynamics alone can generate asset pricing patterns that deviate substantially from the predictions of traditional single-factor models.

B.2 Portfolios Based on Economy Characteristics

Table B.2 presents the summary statistics for global single-sorted stock portfolios based on economy-level characteristics. Consistent with international trade theory, firms in the highest TECH portfolio (Q5) tend to be larger and less disciplined by the force of comparative advantage compared to stocks in the lowest TECH portfolio (Q1). The mean *Market value of equity* for Q5 is roughly $1.95 billion, while the mean *Market value of equity* for Q1 is approximately $364 million. The mean *Industry-adjusted return on equity* for Q5 is approximately −307%, while the mean *Industry-adjusted return on equity* for Q1 is nearly 1062%. In addition, firms in the highest TDPRT portfolio (Q5) with the greatest trade protection tend to be more profitable compared to competitors. In contrast, firms in the lowest TDPRT portfolio (Q1) are more vulnerable to global

competition. The mean *Industry-adjusted return on equity* for Q5 is roughly 348%; while the mean *Industry-adjusted return on equity* for Q1 is approximately −477%.

B.3 Robustness: Distinguishing Factor Contamination from Alternative Explanations

This section presents robustness tests to distinguish factor contamination from alternative explanations for the state-dependent patterns documented in Table 5. Section B.3.1 develops a conceptual framework that differentiates factor contamination from generic state-invariant and state-dependent omitted factors, and clarifies the empirical predictions that separate these explanations. Section B.3.2 examines whether displacement-period market exposures vary systematically with competitive position and market weighting. Section B.3.3 considers whether a flexible single-factor model can account for this paper's empirical results.

B.3.1. *Conceptual Framework and Empirical Predictions*

In explaining the omitted-variables problem of the world CAPM in time-series portfolio regressions, three alternatives arise: (a) generic state-invariant omitted factors, (b) generic state-dependent omitted factors, and (c) factor contamination (i.e., a structured state-dependent omitted factor explanation).

Under a generic state-invariant omitted factor explanation, there are missing factors with constant risk premia and factor loadings across all states. Such omissions would generate persistent pricing errors or constant distortions in factor loadings, but would not produce state-contingent patterns.

Under a generic state-dependent omitted factor explanation, there are missing factors whose risk premia or loadings vary with macroeconomic conditions or investor preferences, while the market factor itself is treated as exogenously and correctly measured. In this scenario, state dependence reflects external variation rather than changes in factor construction.

Under the structured state-dependent omitted factor explanation of factor contamination, competitive displacement induces state-dependent changes in the cross-sectional structure of returns. As dominant firms gain market share and vulnerable firms lose ground, aggregate market returns covary systematically with displacement-sensitive payoffs. This mechanism does not depend on market weighting: even under equal weighting, the market portfolio reflects the altered covariance structure of returns generated by competitive displacement. Value-weighting amplifies the effect by placing greater emphasis on firms whose competitive positions improve during displacement, but it is not the source of contamination. Consequently, equal weighting attenuates, but does not eliminate, factor contamination, because the underlying driver is competitive displacement rather than the choice of market weighting.

The empirical pattern documented in Table 5—stable market betas alongside shifting IAROE exposures concentrated during displacement episodes—is inconsistent with generic state-invariant omitted factors, compatible with generic state-dependent omitted factors, and a direct implication of contamination through competitive displacement. While contamination is a form of state-dependent omission, it generates distinctive empirical predictions that generic state-dependent factor models do not produce naturally.

Specifically, factor contamination implies that market exposures should (i) be contingent on displacement periods rather than appearing uniformly across all states; (ii) vary systematically across portfolios sorted by competitive position (i.e., relative profitability), with divergence concentrated at competitive extremes; and (iii) vary systematically with market construction, exhibiting stronger heterogeneity under value-weighting than equal-weighting. Section B.3.2 tests these predictions.

B.3.2. *Market Weighting and Competitive Heterogeneity During Displacement*

Table B.5 implements tests of the three empirical predictions derived in Section B.3.1. In Panel A, I estimate the marginal market exposure for displacement periods under separate value-weighted and equal-weighted specifications to assess heterogeneity across relative profitability portfolios (predictions i and ii). Panel B employs a value-weight margin specification to test whether this heterogeneity varies systematically with market weighting (prediction iii).

In Table B.5, Panel A estimates a system of time-series portfolio regressions for the five IAROE portfolios (IAROE1–IAROE5) using a "stacked" general method of moments (GMM) estimator. Each portfolio's return is regressed on the market factor, a displacement-period indicator, and their interaction, with the interaction term measuring the displacement-period margin in market exposure. Stacking the system allows for joint inference across portfolios.

Panel A shows that market factor coefficients for the displacement-period margin exhibit pronounced heterogeneity across relative profitability portfolios for the value-weighted construction (GMKT) and the equal-weighted construction (GMKTEW). Under equal weighting, a joint test of heterogeneity strongly rejects equality across IAROE quintiles with a $\chi^2(4)$ of 38.36 and a p-value less than 0.001. Heterogeneity is even more pronounced under value weighting, where the corresponding test yields a $\chi^2(4)$ of 48.05 with a p-value less than 0.001.

Under an equal-weighted construction, market factor coefficients for the displacement-period margin display a divergence across competitive positions. Dominant firms (IAROE5, IAROE4) experience positive displacement effects, indicating greater marginal market exposure during displacement periods, while vulnerable firms (IAROE2, IAROE1) exhibit negative effects. This divergence is captured by a spread test (IAROE5 + IAROE4 - IAROE2 - IAROE1) which produces an estimate of roughly 0.201, which is statistically significant at the 10% level. The

divergence is amplified under value weighting, where the corresponding spread increases to approximately 0.246 and is statistically significant at the 5% level.

Panel B of Table B.5 also estimates a system of time-series portfolio regressions for the five IAROE portfolios (IAROE1–IAROE5) using a stacked GMM estimator. In addition to the equal-weighted market factor, a displacement-period indicator, and their interaction, each portfolio's return is regressed on the value-weighted marginal market factor (i.e., the difference between the value-weighted and equal-weighted market returns) along with its interaction with the displacement-period indicator. This specification isolates the incremental effect of value-weighting on the marginal market exposure for displacement periods, which allows for a test of whether the heterogeneity documented in Panel A varies systematically with market weighting.

Panel B reports the results from this specification. The joint test rejects that value-weighting adds no incremental displacement-period margin effect beyond equal-weighting with a $\chi^2(5)$ of 13.65 and a p-value of roughly 0.018. Additionally, the incremental spread is approximately 1.580 and is statistically significant at the 5% level. The finding suggests that value-weighting systematically amplifies the divergence between dominant and vulnerable firms during competitive displacement periods beyond what occurs under equal-weighting.

Taken together, the results in Table B.5 support the empirical predictions developed in Section B.3.1. The marginal market exposure for displacement periods varies systematically with relative profitability and exhibits a clear sensitivity to market weighting. Hence market exposure is contingent on displacement episodes (prediction i), varies systematically with competitive position (prediction ii), and exhibits sensitivity to the weighting of the market factor (prediction iii). Moreover, the divergence between dominant and vulnerable firms during competitive displacement periods under equal weighting, albeit attenuated, suggests that competitive

displacement alters the cross-sectional structure of returns regardless of market weighting.

B.4 Robustness: Asset Pricing Tests

This section presents robustness tests to verify that the paper's main findings in Table 6 are not confined to one specific set of test assets. Section B.4.1 conducts pricing tests using economy–size portfolios. Section B.4.2 positions SIZE and IAROE relative to global Fama-French factors using correlations and spanning regressions, establishing that both factors retain substantial independent variation beyond SMB and RMW. Section B.4.3 reports pricing tests using global Fama–French portfolios sorted on size and additional firm characteristics, and compares the performance of the world multifactor model with that of the world Fama–French five-factor (FF5) model using economy–industry portfolios for developed markets. Section B.4.4 validates the conditioning instruments used in the conditional asset-pricing tests by comparing them to artificial instrument sets with similar time-series properties but no economic content.

B.4.1. *Economy-Size Portfolios*

Table B.6 presents estimation results for the GMM asset pricing tests using 20 economy–size portfolios constructed by sorting stocks on economy and firm size. These portfolios provide an alternative to the paper's industry-based construction for test assets. The sample covers developed and other markets for the months July 1991 to June 2024.

The world CAPM produces an adjusted R^2 of roughly 0.026, and a UHJM of 0.562 with a simulated p-value of 0.063. In contrast, the world multifactor model achieves an adjusted R^2 of approximately 0.802, representing a substantial improvement in cross-sectional fit. In addition, the UHJM falls to 0.378 with a bootstrapped p-value of 0.235. The IAROE factor is strongly priced with a large SDF loading, while the loading of the market factor is notably attenuated. These results for economy-size portfolios are consistent with the main findings using economy-industry test

portfolios.

Figure B.4 presents scatter plots of mean portfolio returns against average factor betas for the economy-size portfolios. Panel A shows the relation for average GMKT and SIZE betas, while Panel B displays the relation for average IAROE and CRX betas. Each panel includes two specifications: a univariate regression (left y-axis) and the full four-factor model (right y-axis). The plots demonstrate that average IAROE and CRX betas exhibit strong positive relations with average returns in both univariate and multivariate specifications, consistent with the high factor prices in Table B.6. In comparison, the average GMKT beta shows a positive relation only after controlling for the remaining three average betas.

Taken together, the results in Table B.6 and Figure B.4 show that the multifactor model's pricing performance is robust; it is not an artifact of using industry-based test assets.

B.4.2. *Positioning SIZE and IAROE Relative to Global Fama–French Factors*

The competitive displacement framework operates through two firm-level channels affecting global asset prices. First, firm scale determines vulnerability through market breadth: smaller firms serve fewer markets and face greater exposure to competitive erosion. Second, relative profitability reflects vulnerability through cost efficiency: less profitable firms are more susceptible to displacement by cost-efficient competitors.

I construct two corresponding firm-based risk factors to price competitive displacement risk: SIZE captures scale-based vulnerability, while IAROE captures cost-based vulnerability within industries. Although SIZE and IAROE relate to size and profitability dimensions captured by the global Fama–French factors SMB and RMW, my factors differ in construction and economic focus to operationalize this paper's theoretical framework. SIZE is constructed using a global sorting across the full sample of developed and other markets, while SMB uses regional

averaging within developed markets only. To capture the displacement vulnerability margin, IAROE is constructed using the return spread between the most vulnerable and next-vulnerable firms within industries. In contrast, RMW uses a broad robust-minus-weak return spread between extremes.

Table B.7 situates SIZE and IAROE relative to four global Fama–French factors. Panel A of Table B.7 reports correlations between SIZE, IAROE, and the global Fama–French factors. SIZE exhibits a strong correlation of roughly 0.73 with SMB, consistent with both capturing the size dimension. IAROE exhibits only a moderate positive correlation with SMB, reflecting some overlap in the vulnerability to competitive displacement. IAROE is negatively correlated with profitability, value, and investment factors, most notably with RMW. All correlations between IAROE and the Fama-French factors remain moderate in magnitude, with none exceeding 0.50 in absolute terms.

To assess whether SIZE and IAROE contain incremental content beyond existing global factors, I estimate time-series spanning regressions on the global Fama-French factors. Panel B of Table B.7 presents the results. SIZE loads very strongly on SMB with a coefficient of roughly 1.17 that is statistically significant at the 1% level. The finding suggests that both SIZE and SMB capture the global size dimension despite the differences in factor construction. The adjusted R^2 for the spanning regression is approximately 0.54, with an alpha intercept of nearly 1.73 that is statistically significant at the 1% level. This significant intercept shows that in this spanning regression, the mean for SIZE is not absorbed by the global Fama-French factors.

Panel B shows that IAROE exhibits systematic relations with multiple Fama-French factors. The coefficient for RMW is roughly –0.57, and is statistically significant at the 1% level. The finding suggests that both IAROE and RMW relate to a common profitability dimension

despite differences in factor construction. Vulnerable firms (i.e., high IAROE) tend to have weak profitability (i.e., low RMW). Importantly, the adjusted R^2 for the IAROE spanning regression is nearly 0.29, which is substantially lower than the corresponding measure for SIZE (0.54). The alpha intercept is roughly 1.18, and is statistically significant at the 1% level. The finding shows that in this spanning regression, the mean for IAROE is not absorbed by the global Fama-French factors.

Taken together, the findings in Table B.7 suggest that both SIZE and IAROE are systematically related to the global Fama-French factors while retaining substantial independent variation.

B.4.3. *The World Fama-French Five Factor Model and Global Fama-French Portfolios*

Table B.10 compares the pricing performance of the world FF5 model and the paper's multifactor model using economy–industry portfolios from developed markets. The FF5 model achieves an adjusted R^2 of roughly 0.064, and a UHJM of 0.388 with a simulated p-value of 0.098. In contrast, the world multifactor model produces an adjusted R^2 of 0.567 and a nearly identical UHJM of 0.390 with a simulated p-value of 0.169. However, the critical difference emerges when investigating conditional pricing performance: the multifactor model achieves a CHJM of 0.032, indicating virtually no remaining pricing error once competitive conditions are allowed to vary across states. This superior conditional performance reflects not merely the use of conditioning information, but rather the use of conditioning instruments (PC1, PC2, PC3 derived from TECH and TDPRT) that are theoretically motivated by competitive displacement. These instruments capture shifts in product market competition. The FF5 model lacks economically meaningful conditioning variables tied to international competitive dynamics and therefore cannot capture the state-dependent nature of displacement risk (see Panel A of Figure 6).

The factor price and SDF loading estimates in Table B.10 reveal fundamental differences in how the two models capture systematic risk. For GMKT, the FF5 model estimates a factor price of 0.807% per month and a positive SDF loading of 0.045. Both estimates are significant at the 1% level. These results are consistent with traditional CAPM intuition that greater market exposure commands a positive risk premium. In stark contrast, the multifactor model estimates a significantly negative SDF loading and an attenuated factor price. This divergence reflects recognition by the multifactor model that the value-weighted market return is contaminated by winner capture during displacement episodes. This nuanced interpretation is unavailable in the FF5 framework, which treats the global market factor as a clean proxy for systematic risk.

The treatment of size also differs markedly across the two models. In the five-factor model, SMB factor exhibits a significant factor price of roughly 0.451% per month and a significant SDF loading of roughly 0.099, suggesting small firms command a meaningful size premium. However, the SIZE factor in the multifactor model, while showing a significant SDF loading of approximately 0.082, produces an economically small and statistically insignificant factor price of only roughly 0.021% per month. This contrast suggests that the FF5 model, lacking controls for competitive displacement, attributes to SMB what is actually compensation for displacement risk that happens to correlate with firm size.[iii]

The profitability dimension provides perhaps the most striking contrast. The FF5 model includes RMW (profitability), which shows an insignificant factor price of roughly 0.057%. The multifactor model instead employs IAROE, which captures industry-adjusted profitability and commands a substantial factor price (roughly 1.535% per month) along with an SDF loading of approximately 0.289. Both estimates are significant at the 1% level. The economic mechanism

[iii] See Section B.4.2 and Table B.7. SIZE and IAROE load on SMB in factor-spanning regressions.

explains the contrast: IAROE measures competitive displacement risk by identifying firms with low profitability relative to their industry peers, while RMW measures absolute profitability without accounting for industry-specific product market competition. The findings in Table B.10 suggest that relative profitability is the economically relevant dimension for pricing displacement risk, and that an absolute profitability factor may not capture displacement risk. Moreover, the world FF5 model— like the world CAPM —may conflate multiple economic mechanisms and fail to capture the state-dependent nature of competitive displacement when estimating equity risk premia.

To further explore the robustness of the world multifactor model, I examine its performance on widely used test assets from the international asset pricing literature. Specifically in Table B.11, I evaluate the model using four sets of global Fama-French portfolios: (a) size-operating profitability, (b) size-investment, (c) size-book-to-market, and (d) size-momentum. Whereas the standard portfolios use a five-by-five construction, this paper uses a four-by-five construction (removing quintile 3 in the size dimension) to adhere to the portfolio selection rule in Section A.3.3. The sample covers developed markets for the months July 1990 to June 2024.

The robustness tests in Table B.11 confirm the main findings in Table 6. Across all test asset sets, the world multifactor model achieves a better cross-sectional fit compared to the world CAPM. Overall, the findings suggest that displacement risk is a pervasive source of systematic variation in international equity returns, operating independently of industry classification, geographic grouping, or the specific characteristics used to form test portfolios.

Figures B.7 and B.8 provide additional insight into how displacement risk relates to the Fama-French profitability and investment factors. Figure B.7 shows that low-profitability Fama-French portfolios (DVOX1, where X denotes the size quintile) systematically exhibit low average

IAROE betas, indicating high relative profitability despite low absolute profitability. This counterintuitive pattern reveals a fundamental distinction: a firm can have low absolute profitability yet still maintain a strong competitive position within a low-margin industry. For instance, a company with a 3% ROE may appear unprofitable in absolute terms, but if its industry peers average 2.5%, this firm exhibits high relative profitability and occupies a dominant position within its sector. Consequently, RMW, by sorting on absolute profitability, does not systematically identify competitive vulnerability within industries, capturing displacement risk only indirectly, and only when absolute profitability happens to coincide with relative profitability.

Figure B.8 reveals a complementary pattern: high-investment portfolios (DVIX5, representing aggressive asset growth) exhibit systematically low average IAROE betas, while low-investment portfolios exhibit high average IAROE betas. This pattern is consistent with the view that firms with weak industry-relative profitability tend to face tighter financial constraints, which may limit their ability to invest, whereas dominant firms possess the resources and cash flow to pursue aggressive investment strategies. The CMA factor therefore captures an indirect manifestation of displacement risk through investment intensity, but does not directly identify firms that are vulnerable relative to their industry competitors. Financially constrained firms may lack the resources for reinvestment precisely because these firms are vulnerable, while dominant firms invest aggressively because their relative profitability generates cash flow.

Taken together, Figures B.7 and B.8 suggest that the RMW and CMA factors partially, but imperfectly, account for competitive displacement. RMW relies on absolute profitability and therefore fails to distinguish between vulnerable firms and firms that operate in low-margin industries. CMA reflects investment behavior that correlates with competitive strength, but only indirectly and without isolating competitive vulnerability within industries. In comparison, IAROE

isolates displacement risk explicitly by conditioning on industry-adjusted profitability, yielding a more precise mapping between competitive vulnerability and equity risk premia.

B.4.4. *Validation of Conditioning Instruments*

The conditioning instruments in the conditional asset-pricing tests are three principal components constructed from nonlinear transformations of two economy-based factors, TECH and TDPRT. Given the very low level of the conditional Hansen–Jagannathan metric (CHJM) for developed-economy-industry portfolios in Table 6, one may ask whether such a low value reflects economically meaningful state dependence or could instead be generated mechanically by applying the same principal-components construction to generic persistent factors. The placebo tests below are designed to address this concern directly by holding the asset-pricing model, developed-economy test assets, and CHJM computation fixed, while varying only the factors used to construct the principal-component conditioning instruments.

To implement these tests, I replace the economy-based factors with artificial placebo factors that match key time-series properties of TECH and TDPRT but contain no economic content. These placebo factors are passed through the identical transformations and principal-components procedure used in the baseline specification to construct three conditioning instruments.

The first placebo replaces TECH and TDPRT with two independent AR(1) processes calibrated to match the persistence and unconditional variance of the original factors. The second placebo provides a more demanding test by allowing the artificial factors to exhibit both persistence and comovement. Specifically, I simulate a bivariate VAR(1) process calibrated to match the joint dynamics of TECH and TDPRT, including their autocorrelation and cross-correlation.

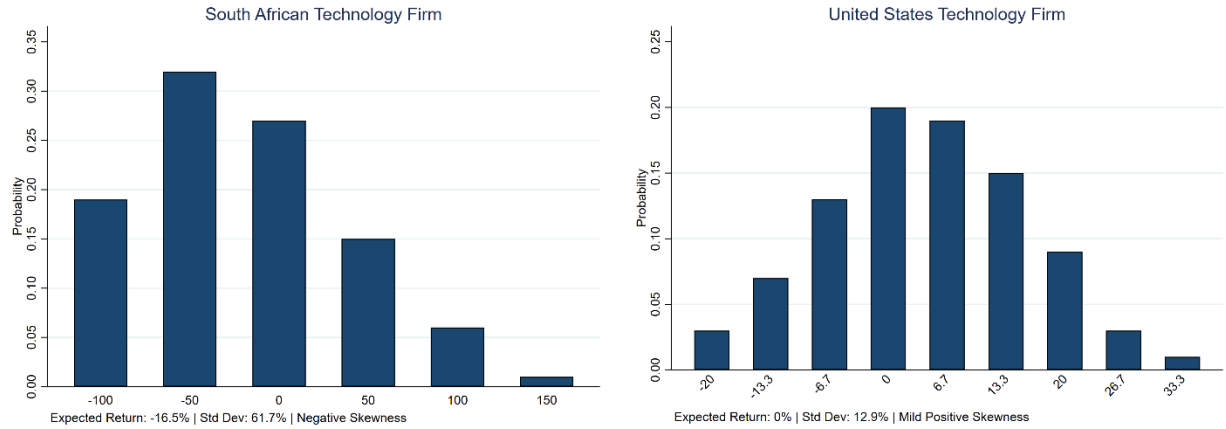
Table B.12 presents the results of the placebo tests. Under the persistence-matched placebo, the CHJM is roughly 0.41, which is much larger than the CHJM of 0.032 in the baseline specification for developed-economy-industry portfolios in Table 6. The finding suggests that persistence alone, combined with the principal-components construction, is insufficient to generate the low CHJM value. Even with matched comovement, the CHJM remains relatively large (nearly 0.28) compared to the baseline figure.

Taken together, the placebo exercises in Table B.12 indicate that the conditional pricing performance documented in Table 6 is not a mechanical consequence of applying a principal-components procedure to persistent or comoving factors. Rather, the very low level of the CHJM appears to be specific to conditioning instruments constructed from economy-based factors that capture economically meaningful variation in competitive conditions.

Figure B.1. Toy Example Returns and Equity Risk Premia

This figure presents a visualization to explain returns and equity risk premia in this paper's toy example. For the technology sector, Panel A shows return distributions for vulnerable firms on the left side (pronounced negative skew) and dominant firms on the right side (mild positive skew). Panel B shows return volatility in the materials sector when supply-side shocks are absent (on the left side) and when there are simultaneous demand-side and supply-side shocks (on the right side).

Panel A: Return Distributions for Vulnerable and Dominant Technology Firms



Panel B: Return Volatility for Materials Firms

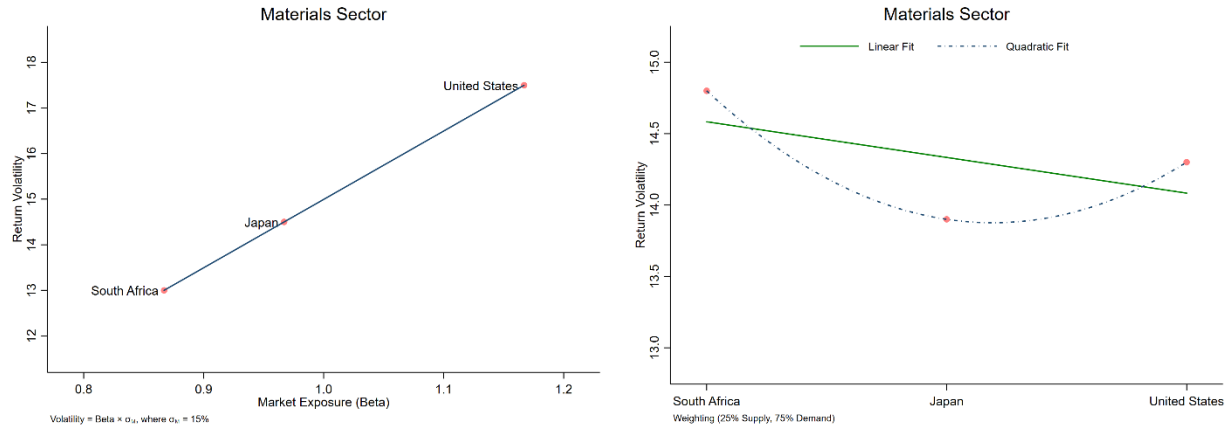


Table B.1. Negative and Insignificant Market Betas in Simulated Economies: The Role of Industry Concentration

This table presents logit regression results for the sample of simulated firms where the left-hand-side (LHS) variable is a binary indicator equal to one if the simulated firm exhibits a negative global market beta (in columns 1 to 6), or a binary indicator equal to one if the simulated firm exhibits a negative global market beta or a global market beta that is not statistically significant. The model parameters, along with the moments for the macroeconomic characteristics are shown in Table 1. The descriptions of the model parameters, macroeconomic characteristics, and model outcomes are presented in Table A.1.

Industry concentration	0.034	0.029	0.032	0.033	0.026	0.027	0.029
	(0.007)**	(0.007)**	(0.007)**	(0.007)**	(0.007)**	(0.007)**	(0.007)**
$\ln\left(2\sum_{n\in\Lambda_{ki,1}} x_{kn,1}\right)$	−0.052	−0.078	−0.050	−0.053	−0.076	−0.079	−0.080
	(0.008)**	(0.010)**	(0.008)**	(0.010)**	(0.009)**	(0.010)**	(0.010)**
$c_{i,1}$		0.010			0.008	0.014	0.015
		(0.009)			(0.009)	(0.008)+	(0.008)+
$\ln\left(Y_{i,1}\right)$		0.000			0.005	−0.005	−0.004
		(0.012)			(0.012)	(0.011)	(0.012)
$\ln(d_n)$		−0.045			−0.046	−0.055	−0.055
		(0.013)**			(0.014)**	(0.011)**	(0.012)**
I(CRX Portfolio = 2)				−0.055		−0.063	−0.067
				(0.034)		(0.025)*	(0.026)**
I(CRX Portfolio = 3)				−0.058		−0.074	−0.081
				(0.030)+		(0.025)**	(0.026)**
I(CRX Portfolio = 4)				−0.091		−0.096	−0.102
				(0.032)**		(0.029)**	(0.029)**
I(CRX Portfolio = 5)				−0.109		−0.131	−0.139
				(0.028)**		(0.023)**	(0.024)**
Trial dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Home economy included	Yes	Yes	No	No	No	No	No
Number of sim. firms	6774	6774	6480	6480	6480	6480	6480
Model *p*-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Coefficients are presented as marginal effects. Robust delta-method standard errors which cluster at the trial-economy level are reported in parentheses. Model *p*-value shows the result for a test that all of the coefficients (excluding the constant) are jointly zero. +, *, ** denote statistical significance at the 10%, 5% and 1% levels.

Figure B.2. Nonlinearity Within Industry-Adjusted Return on Equity (IAROE) Portfolios

This figure presents a median spline regression fit for the relation between *Value-weighted excess return* and the double-sorted IAROE portfolios (IAROE1 to IAROE5). The sample period is from July 1989 to June 2024. The variable definitions [descriptions] are presented in Table 3 [Table A.1].

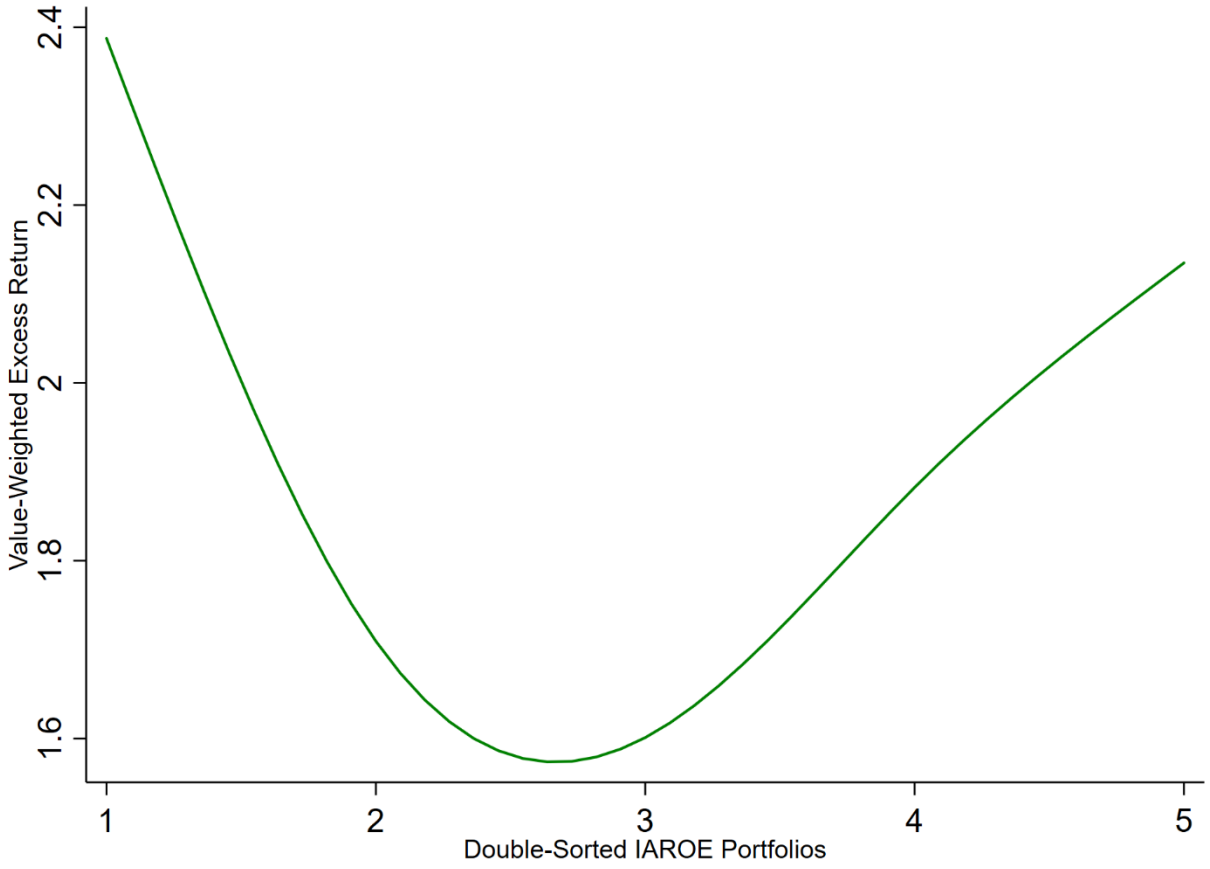


Table B.2. Economy Characteristic Portfolios

This table presents summary statistics for the single-sorted TECH and TDPRT portfolios. The sample period is from July 1989 to June 2024. *Market value of equity* is the total market capitalization of a firm's equity (in June 2024 US dollars). *Excess return* is the monthly return (in US dollars) to buying the stock at time $t - 1$ and then selling it at time t, in excess of the risk-free rate. *Value-weighted excess return* is the weighted mean of *Excess return* for a portfolio where the weight of each stock is its *Market value of equity*. Single-sorted portfolios are created in June of year y for the evaluation of monthly returns from July of year y to June of year $y + 1$. Five portfolios are created based on quintiles for each sorting characteristic (*Market value of equity*, SIZE; *Industry-adjusted return on equity*, IAROE; *Technology*, TECH; *Trade protection*, TDPRT; *Industry profitability dispersion*, IDISP; and *Mean currency excess return*, CRX). *Industry-adjusted return on equity* is the residual from a regression of return on equity (net income divided by total equity) on (two-digit standard industry classification, SIC, code) industry fixed effects for all firms using the full data extraction period (January 1975 to March 2025). *Technology* is a measure of absolute advantage proxied by current gross domestic product (in US dollars). *Trade protection* is a measure of trade protection proxied by the (interpolated) weighted average of the import tariff rate across all products in an economy. *Industry profitability dispersion* is the interquartile range for return on equity within an industry. *Mean currency excess return* is the annual average of the currency excess return in an economy, where the currency excess return is computed as the monthly return (in US dollars) to buying a foreign currency in the forward market (at the forward rate) at time $t - 1$ and then selling it in the spot market (at the spot rate) at time t. For TECH, TDPRT, IDISP and CRX, single-sorted portfolios for portfolio year y are based on the year $y - 1$ value for the characteristic of the economy where the firm is listed. These single-sorted portfolios are used to construct factors as Q5 – Q1 long-short factor mimicking portfolios. Single-sorted portfolios for SIZE and IAROE are created in June of year y for summary statistics (using *Market value of equity* in June of year y and *Industry-adjusted return on equity* in December of year $y - 1$). Double-sorted portfolios for SIZE and IAROE are also created in June of year y for evaluation of monthly returns from July of year y to June of year $y + 1$. Two portfolios for SIZE are first created based on the median cutoff of *Market value of equity* in June of year y. Within each of these SIZE portfolios, five portfolios for IAROE (P1 to P5 for the low SIZE portfolio, and P6 to P10 for the high SIZE portfolio) are created based on quintiles for *Industry-adjusted return on equity* in December of year $y - 1$. These double-sorted portfolios are used to construct factors as long-short portfolio return averages. The SIZE factor is the average return of P6 to P10 (SIZE2) minus the average return of P1 to P5 (SIZE1). The IAROE factor is the average return of P1 and P6 (IAROE1) minus the average return of P2 and P7 (IAROE2). *Global market factor* (GMKT) is the monthly return (in US dollars) of the global Morgan Stanley Capital International (MSCI) index in excess of the risk-free rate. *Local market factor* (LMKT) is the weighted mean of *Excess return* for all firms in an economy where the weight of each stock is its *Market value of equity*. Newey and West (1987) standard errors with optimal lag selection are estimated and reported in parentheses. Variable descriptions are presented in Table A.1.

TECH Portfolio	Q1	Q2	Q3	Q4	Q5
Value-weighted excess return	1.163	0.986	0.890	0.728	0.846
	(0.446)	(0.253)	(0.225)	(0.381)	(0.152)
Market value of equity (mean)	364.05	877.23	878.33	1320.79	1948.25
Industry-adjusted return on equity (mean)	1061.94	676.26	534.07	229.48	−307.31
Number of firms (mean)	493	1292	2252	4294	24331
Average single-sorted SIZE portfolio	2.41	2.82	2.79	2.60	3.20
Average single-sorted IAROE portfolio	3.08	3.04	3.05	3.04	2.99
Average single-sorted TDPRT portfolio	2.68	2.37	2.47	3.15	2.27
Average single-sorted CRX portfolio	3.36	2.87	2.75	2.90	2.77

TDPRT Portfolio	Q1	Q2	Q3	Q4	Q5
Value-weighted excess return	0.845	0.456	0.990	1.078	1.078
	(0.181)	(0.367)	(0.258)	(0.386)	(0.334)
Market value of equity (mean)	1835.47	1535.28	1432.02	1674.55	1585.73
Industry-adjusted return on equity (mean)	−476.95	−5.21	282.02	365.66	348.40
Number of firms (mean)	15428	6894	4302	4677	2966
Average single-sorted SIZE portfolio	3.11	3.07	3.06	3.11	2.55
Average single-sorted IAROE portfolio	3.02	2.82	3.06	3.02	3.12
Average single-sorted TECH portfolio	4.36	4.40	3.86	4.07	4.26
Average single-sorted CRX portfolio	2.78	2.54	2.92	2.70	2.92

Table B.3. Explaining Fim Size and Industry Dispersion Anomalies

This table presents results for time-series portfolio regressions. For each regression, Newey and West (1987) standard errors with optimal lag selection are estimated with absolute *t*-statistics reported in parentheses. +, *, ** denote statistical significance at the 10%, 5% and 1% levels. The sample period is from July 1989 to June 2024. The variable definitions [descriptions] are presented in Table 3 [Table A.1].

Panel A

SIZE Portfolio	Q1	Q2	Q3	Q4	Q5	Q1 – Q5
Market factor	0.491	0.516	0.498	0.534	0.650	−0.159
	(11.988)**	(17.701)**	(15.976)**	(14.812)**	(20.106)**	(3.657)**
SIZE	0.539	0.575	0.448	0.248	−0.088	0.628
	(5.530)**	(9.177)**	(8.492)**	(5.463)**	(2.730)**	(4.650)**
IAROE	0.319	0.118	0.133	0.091	0.137	0.181
	(2.313)*	(2.014)*	(1.738)+	(1.364)	(1.859)+	(2.435)*
TECH	−0.088	−0.002	0.018	0.038	0.083	−0.171
	(1.757)+	(0.057)	(0.626)	(1.299)	(2.418)*	(3.466)**
TDPRT	0.056	0.006	−0.013	−0.006	0.142	−0.086
	(1.955)+	(0.653)	(1.658)+	(0.328)	(2.175)*	(1.186)
CRX	0.059	−0.017	−0.010	−0.017	0.005	0.053
	(1.629)	(0.818)	(0.639)	(0.798)	(0.306)	(1.755)+
Alpha	1.017	0.352	0.091	0.306	0.520	0.498
	(5.477)**	(3.781)**	(0.822)	(2.925)**	(4.851)**	(2.134)*
Number of periods	420	420	420	420	420	420

Panel B

IDISP Portfolio	Q1	Q2	Q3	Q4	Q5	Q5 – Q1
Market factor	0.770	0.746	0.770	0.651	0.733	−0.037
	(30.896)**	(18.787)**	(27.524)**	(13.750)**	(25.789)**	(1.389)
SIZE	−0.120	−0.014	−0.008	−0.070	−0.036	0.084
	(2.626)**	(0.495)	(0.215)	(1.591)	(0.635)	(1.056)
IAROE	−0.109	−0.102	0.162	0.290	0.388	0.498
	(2.111)*	(1.826)+	(3.573)**	(2.593)**	(4.697)**	(5.028)**
TECH	−0.036	0.013	0.065	0.091	0.058	0.093
	(2.062)*	(0.334)	(2.225)*	(1.631)	(1.648)+	(2.489)*
TDPRT	−0.023	0.029	−0.002	−0.022	−0.006	0.017
	(2.265)*	(0.850)	(0.133)	(2.314)*	(0.485)	(1.338)
CRX	−0.017	0.016	0.050	0.008	0.029	0.045
	(1.223)	(0.687)	(2.760)**	(0.285)	(1.198)	(1.970)*
Alpha	0.522	0.368	0.551	0.476	0.452	−0.071
	(5.313)**	(3.628)**	(5.986)**	(4.563)**	(3.213)**	(0.433)
Number of periods	420	420	420	420	420	420

Table B.4. Explaining the Industry Dispersion Anomaly During Normal and Displacement Periods

This table presents results for time-series portfolio regressions. For each regression, Newey and West (1987) standard errors with optimal lag selection are estimated with absolute *t*-statistics reported in parentheses. +, *, ** denote statistical significance at the 10%, 5% and 1% levels. The sample period is from July 1989 to June 2024. The variable definitions [descriptions] are presented in Table 3 [Table A.1].

Panel A

IDISP Portfolio	Q5 – Q1		Q5 – Q1	
Market factor	0.006	0.204	−0.057	0.012
	(0.148)	(3.456)**	(1.974)*	(0.128)
SIZE			0.120	−0.178
			(1.717)+	(1.277)
IAROE			0.457	0.862
			(4.704)**	(3.775)**
TECH			0.099	0.036
			(2.464)*	(0.576)
TDPRT			0.015	−0.036
			(1.362)	(0.330)
CRX			0.047	0.089
			(2.052)*	(0.826)
Alpha	0.489	0.362	−0.078	−0.216
	(2.535)*	(1.335)	(0.440)	(0.620)
Period type	Normal	Displacement	Normal	Displacement
Number of periods	377	43	377	43

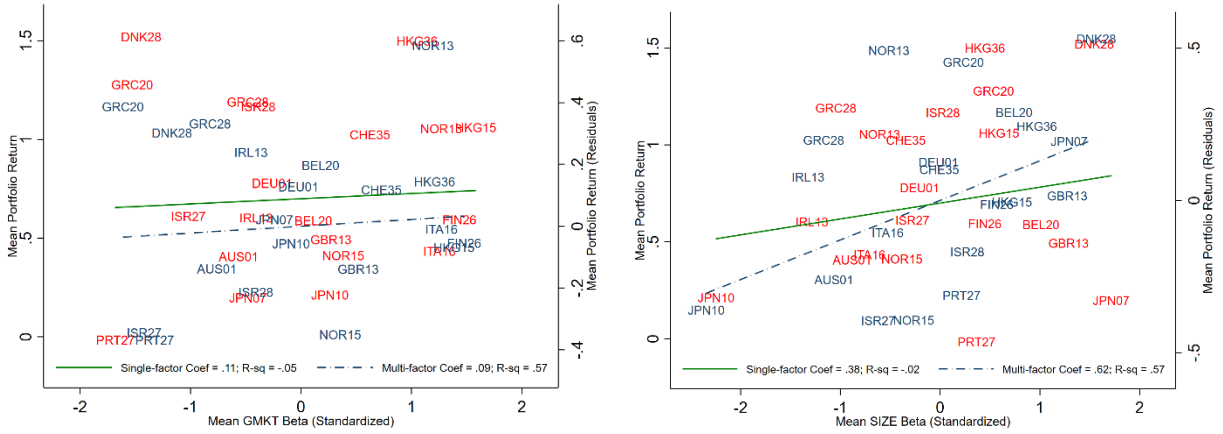
Panel B

IDISP Portfolio	Q5 – Q1
Market factor	−0.051
	(1.756)+
SIZE	0.122
	(1.879)+
SIZE (displacement margin)	−0.353
	(2.835)**
IAROE	0.454
	(4.471)**
IAROE (displacement margin)	0.498
	(2.258)*
TECH	0.099
	(2.931)**
TECH (displacement margin)	−0.056
	(0.746)
TDPRT	0.016
	(1.301)
TDPRT (displacement margin)	−0.015
	(0.145)
CRX	0.047
	(2.118)*
CRX (displacement margin)	0.023
	(0.220)
Alpha	−0.083
	(0.492)
Alpha (displacement margin)	−0.090
	(0.257)
Number of periods	420

Figure B.3. Global Multifactor Betas and Economy-Industry Portfolios: Developed Markets Only

This figure presents a linear regression fit and a scatter plot for the cross-sectional relation between the mean monthly portfolio return and the average generalized method of moments (GMM) estimate of the factor exposure (or beta) for the test assets in a multifactor model. The test assets are the 20 economy-industry portfolios (with plot markers XXXNN where XXX represents the economy code and NN represents the two-digit standard industry classification, SIC, code). There are four factors. Panel A presents results for the mean GMKT and SIZE factor betas, while Panel B shows the results for the mean IAROE and CRX factor betas. Each image shows two y-axes. The y-axis on the left represents the results using a specification limited to the single beta shown on the x-axis, while the y-axis on the right represents the results using a specification with all four mean factor betas. Mean betas on the x-axis are standardized to show consistent estimates across both y-axes. The sample period is from July 1989 to June 2024. The variable definitions [descriptions] are presented in Table 3 [Table A.1]. Summary statistics for the economy-industry portfolios are shown in Table A.2.

Panel A: GMKT and SIZE Factor Betas



Panel B: IAROE and CRX Factor Betas

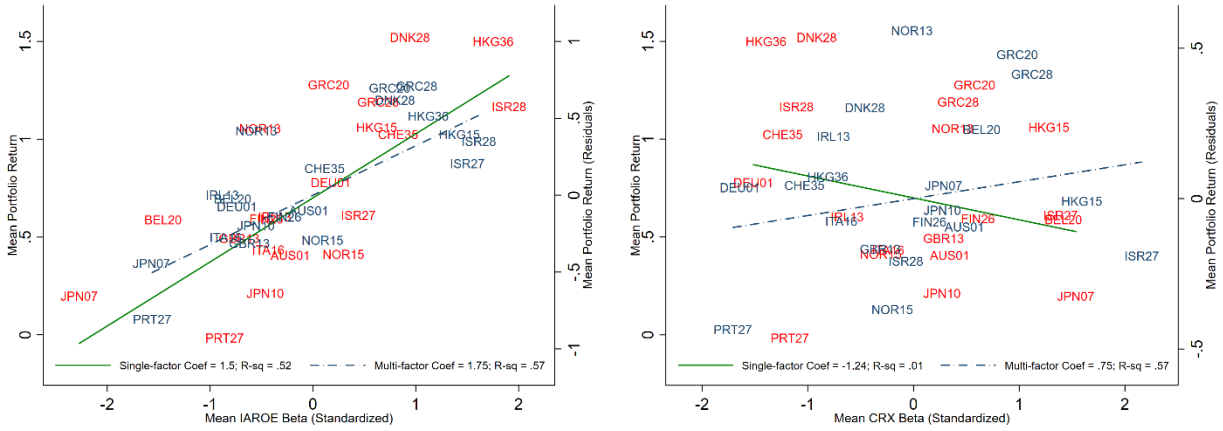


Table B.5. Market Weighting and Competitive Heterogeneity During Displacement Periods

This table presents results for three time-series portfolio regression systems using a generalized method of moments (GMM) procedure with optimal weights (two in Panel A; one in Panel B). For each regression, Newey and West (1987) standard errors with optimal lag selection are estimated with absolute *t*-statistics reported in parentheses. +, *, ** denote statistical significance at the 10%, 5% and 1% levels. The sample period is from July 1989 to June 2024. The variable definitions [descriptions] are presented in Table 3 [Table A.1].

Panel A: State-Dependent Market Exposure Under Alternative Market Weighting

IAROE Portfolio	IAROE1	IAROE2	IAROE3	IAROE4	IAROE5		
GMKTEW Estimates						Spread	Het.
Market factor	1.004	0.870	0.817	0.855	0.850		
	(40.172)**	(38.690)**	(39.703)**	(36.509)**	(32.550)**		
Market factor (disp. margin)	−0.050	−0.140	−0.094	−0.011	0.022	0.201	38.360
	(0.665)	(4.984)**	(2.310)*	(0.340)	(0.625)	[0.059]+	[0.000]**
Alpha	1.887	1.163	1.043	1.261	1.657		
	(7.779)**	(7.797)**	(11.773)**	(9.930)**	(9.827)**		
Alpha (disp. margin)	0.074	−0.084	0.057	0.050	−0.030		
	(0.156)	(0.275)	(0.178)	(0.154)	(0.082)		
Number of periods							420

Spread denotes the IAROE5 + IAROE4 – IAROE2 – IAROE1 estimate in the corresponding row. *p*-values are reported in brackets for the null hypothesis that the spread is equal to zero. Heterogeneity (Het.) denotes the Chi-squared statistic for the null hypothesis (Wald test) that all of the estimates in the corresponding row are equal, with *p*-values reported in brackets.

IAROE Portfolio	IAROE1	IAROE2	IAROE3	IAROE4	IAROE5		
GMKT Estimates						Spread	Het.
Market factor	0.989	0.859	0.800	0.842	0.831		
	(27.683)**	(39.958)**	(47.169)**	(38.667)**	(32.558)**		
Market factor (disp. margin)	−0.046	−0.131	−0.066	0.017	0.053	0.246	48.050
	(0.600)	(3.769)**	(1.206)	(0.390)	(1.133)	[0.008]**	[0.000]**
Alpha	1.888	1.162	1.046	1.262	1.662		
	(7.908)**	(7.466)**	(10.681)**	(9.620)**	(9.962)**		
Alpha (disp. margin)	−0.223	−0.308	−0.166	−0.207	−0.299		
	(0.417)	(0.827)	(0.612)	(0.719)	(0.998)		
Number of periods							420

Spread denotes the IAROE5 + IAROE4 – IAROE2 – IAROE1 estimate in the corresponding row. *p*-values are reported in brackets for the null hypothesis that the spread is equal to zero. Heterogeneity (Het.) denotes the Chi-squared statistic for the null hypothesis (Wald test) that all of the estimates in the corresponding row are equal, with *p*-values reported in brackets.

Panel B: Incremental Value-Weighted Divergence Across Relative Profitability Portfolios

IAROE Portfolio	IAROE1	IAROE2	IAROE3	IAROE4	IAROE5		
Value-Weight Margin Estimates						Inc. spread	Het.
Market factor	1.010	0.876	0.820	0.860	0.853		
	(35.845)**	(41.384)**	(45.239)**	(41.797)**	(35.455)**		
Market factor (disp. margin)	−0.067	−0.147	−0.086	−0.001	0.031		
	(0.928)	(5.767)**	(1.952)+	(0.043)	(0.875)		
Market factor (weight margin)	0.352	0.345	0.179	0.281	0.161		
	(1.911)+	(4.953)**	(2.147)*	(1.819)+	(0.906)		
Market factor (both margins)	−0.738	−0.402	0.175	0.198	0.241	1.580	13.650
	(2.588)**	(1.523)	(1.110)	(1.059)	(1.050)	[0.010]**	[0.018]*
Alpha	1.880	1.156	1.039	1.255	1.654		
	(7.880)**	(7.719)**	(11.740)**	(9.982)**	(9.955)**		
Alpha (disp. margin)	0.193	−0.060	−0.042	−0.083	−0.143		
	(0.367)	(0.165)	(0.153)	(0.307)	(0.526)		
Number of periods							420

Incremental (Inc.) spread denotes the IAROE5 + IAROE4 – IAROE2 – IAROE1 estimate in the corresponding row. *p*-values are reported in brackets for the null hypothesis that the difference of margin is equal to zero. Heterogeneity (Het.) denotes the Chi-squared statistic for the null hypothesis (Wald test) that all of the estimates in the corresponding row are equal, with *p*-values reported in brackets.

Table B.6. Performance Tests Using Economy-Size Portfolios

This table presents results for asset pricing tests using a generalized method of moments (GMM) procedure with optimal weights. The test assets are 20 economy-size portfolios. For developed and other markets, the sample period is from July 1991 to June 2024. The variable definitions [descriptions] are presented in Table 3 [Table A.1].

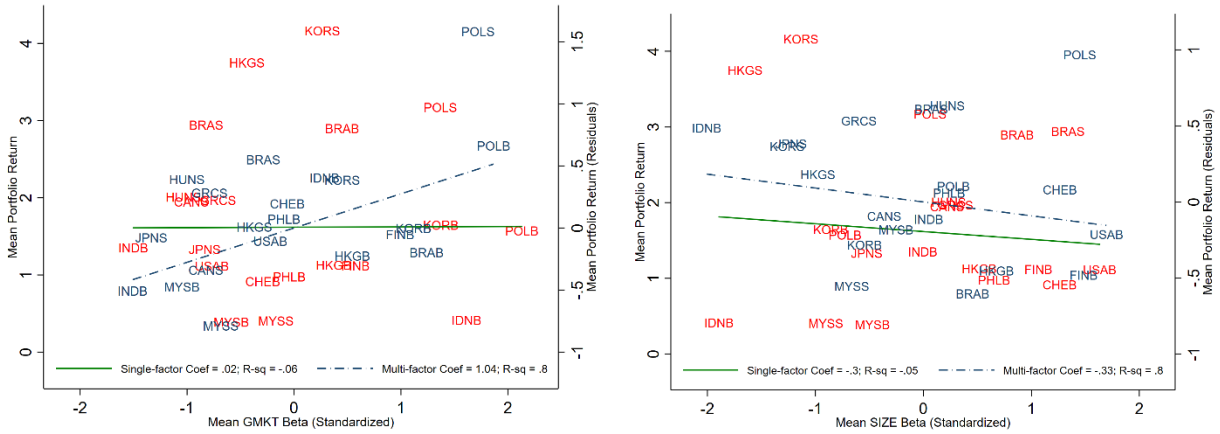
Factor	**GMKT**	**SIZE**	**IAROE**	**CRX**			
World CAPM Two-step GMM (Optimal) Estimates					A.R-sq		UHJM
			Developed and Other Markets				
Factor price	1.808				0.026		0.562
	[0.000]**						[0.063]+
SDF loading	0.086						
	[0.000]**						
World Multifactor Two-step GMM (Optimal) Estimates					A.R-sq	Hansen J	UHJM/CHJM
			Developed and Other Markets				
Factor price	1.449	0.078	1.589	1.368	0.802	14.865	0.378
	[0.000]**	[0.025]*	[0.000]**	[0.000]**		[1.000]	[0.235]
SDF loading	0.020	0.075	0.275	0.088			0.265
	[0.000]**	[0.000]**	[0.000]**	[0.000]**			[0.474]

I estimate Newey and West (1987) standard errors with optimal lag selection. *p*-values are reported in brackets. UHJM and CHJM denote the unconditional and conditional Hansen–Jagannathan metrics, respectively, computed as the Hansen–Jagannathan norm of the pricing-error vector evaluated at the optimal GMM estimates. The reported statistics test the null hypothesis that the corresponding pricing-error measure is equal to zero. Hansen J denotes the Hansen (1982) J statistic for the null hypothesis that the overidentifying restrictions are valid. A.R-sq is the adjusted R-squared from a cross-sectional regression of average excess returns on the mean factor exposure (or beta) estimates. +, *, ** denote statistical significance at the 10%, 5% and 1% levels.

Figure B.4. Global Multifactor Betas and Economy-Size Portfolios: Developed and Other Markets

This figure presents a linear regression fit and a scatter plot for the cross-sectional relation between the mean monthly portfolio return and the average generalized method of moments (GMM) estimate of the factor exposure (or beta) for the test assets in a multifactor model. The test assets are the 20 economy-size portfolios (with plot markers XXXY where XXX represents the economy code and Y uses S for smaller firms and B for larger firms within each economy). There are four factors. Panel A presents results for the mean GMKT and SIZE factor betas, while Panel B shows the results for the mean IAROE and CRX factor betas. Each image shows two y-axes. The y-axis on the left represents the results using a specification limited to the single beta shown on the x-axis, while the y-axis on the right represents the results using a specification with all four mean factor betas. Mean betas on the x-axis are standardized to show consistent estimates across both y-axes. The sample period is from July 1991 to June 2024. The variable definitions [descriptions] are presented in Table 3 [Table A.1].

Panel A: GMKT and SIZE Factor Betas



Panel B: IAROE and CRX Factor Betas

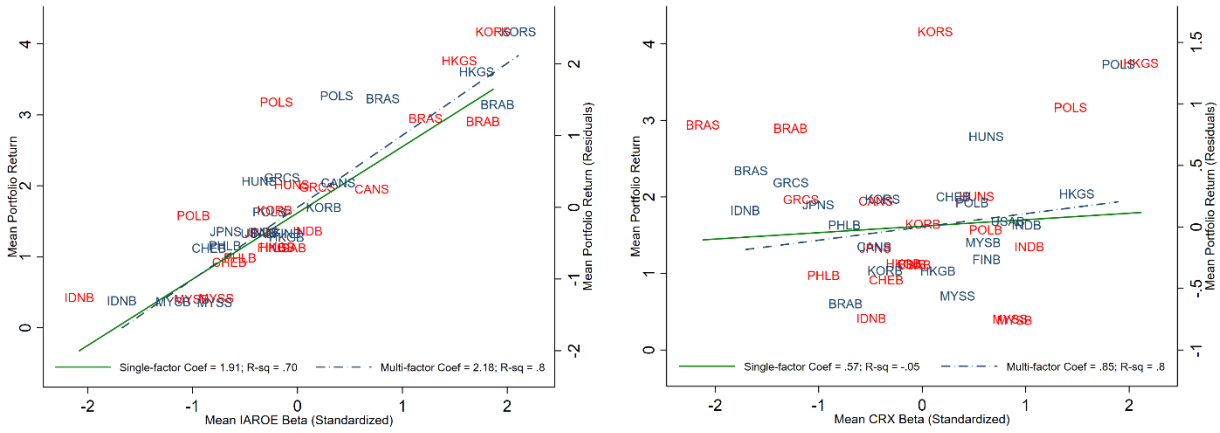


Figure B.5. Conditioning Factors During Normal and Displacement Periods

This figure presents a time-series plot of the twelve-month moving average for the global factors used for conditioning instruments in this paper. The conditioning instruments are three principal component scores (PC1, PC2, and PC3) derived from the dynamics of the technology factor (TECH) and the trade protection factor (TDPRT). Six major episodes of product market displacement are identified as structural breaks: the Mexican peso crisis (MPS), the Asian financial crisis (AFC), the dot-com bust (DCB), the great trade collapse following the global financial crisis (GFC), the taper tantrum (TTM), and the US-China trade war (TRD). The sample period is from July 1989 to June 2024. The variable definitions [descriptions] are presented in Table 3 [Table A.1].

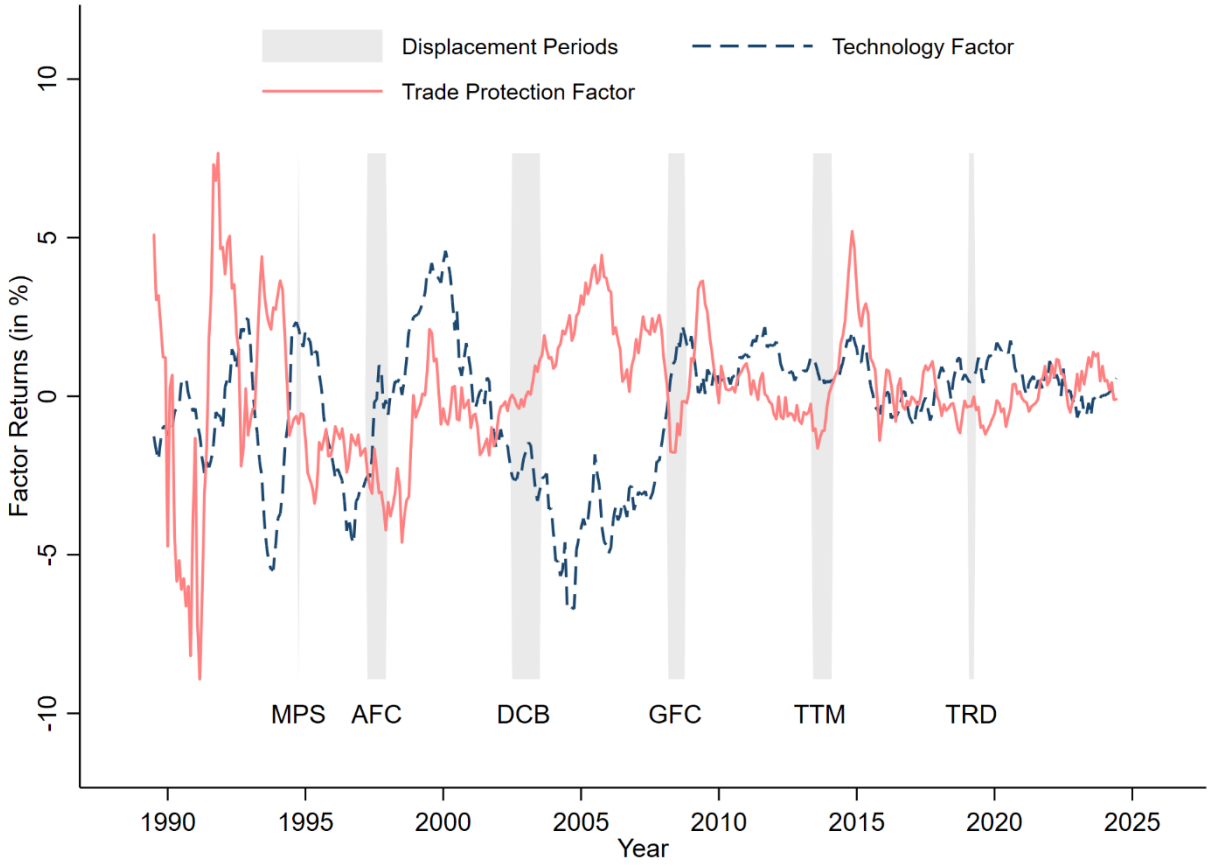


Table B.7. Positioning Firm-Based Factors Relative to Global Fama–French Factors

This table presents factor correlations in Panel A, and the results for two time-series factor-spanning regressions in Panel B. The sample period is from July 1990 to June 2024. The variable definitions [descriptions] are presented in Table 3 [Table A.1].

Panel A: Global Fama French Factor Correlations

	SIZE	IAROE	SMB	HML	RMW	CMA
SIZE	1.0000					
IAROE	0.2971*	1.0000				
SMB	0.7320*	0.2371*	1.0000			
HML	0.0089	−0.2941*	0.0875	1.0000		
RMW	−0.1181*	−0.3973*	−0.2888*	−0.0142	1.0000	
CMA	−0.0514	−0.3671*	−0.0250	0.7401*	0.0891	1.0000

Panel B: Factor-Spanning Regressions

Factors	SIZE	IAROE
SMB	1.171	0.190
	(13.263)**	(2.483)*
HML	−0.065	−0.139
	(0.896)	(2.119)*
RMW	0.204	−0.569
	(3.358)**	(5.003)**
CMA	0.002	−0.293
	(0.025)	(2.285)*
Alpha	1.726	1.117
	(12.421)**	(6.958)**
OLS Adjusted R-sq	0.544	0.287
Number of periods	408	408

Newey and West (1987) standard errors with optimal lag selection are estimated with absolute *t*-statistics reported in parentheses. OLS Adjusted R-sq is the adjusted R-squared from time-series regression. +, *, ** denote statistical significance at the 10%, 5% and 1% levels.

Table B.8. Explaining Fim Size and Industry Dispersion Anomalies Using the World Fama-French Five Factor Model

This table presents results for time-series portfolio regressions. For each regression, Newey and West (1987) standard errors with optimal lag selection are estimated with absolute *t*-statistics reported in parentheses. +, *, ** denote statistical significance at the 10%, 5% and 1% levels. The sample period is from July 1990 to June 2024. The variable definitions [descriptions] are presented in Table 3 [Table A.1].

Panel A

SIZE Portfolio	Q1	Q2	Q3	Q4	Q5	Q1 – Q5
Market factor	0.450	0.479	0.487	0.536	0.651	−0.200
	(11.057)**	(22.205)**	(21.626)**	(15.251)**	(7.548)**	(2.443)*
SMB	0.735	0.709	0.671	0.510	−0.078	0.812
	(5.414)**	(10.175)**	(9.660)**	(11.943)**	(1.638)	(5.223)**
HML	−0.207	−0.209	−0.304	−0.294	−0.172	−0.035
	(1.732)+	(3.310)**	(4.813)**	(5.663)**	(1.532)	(0.257)
RMW	−0.165	−0.031	−0.070	−0.076	−0.131	−0.034
	(1.356)	(0.445)	(0.842)	(1.063)	(0.903)	(0.214)
CMA	−0.132	−0.026	0.102	0.115	−0.096	−0.036
	(1.004)	(0.400)	(1.513)	(1.283)	(0.729)	(0.239)
Alpha	2.497	1.533	1.034	0.836	0.592	1.906
	(7.625)**	(10.461)**	(6.734)**	(6.687)**	(4.257)**	(6.324)**
Number of periods	408	408	408	408	408	408

Panel B

IDISP Portfolio	Q1	Q2	Q3	Q4	Q5	Q5 – Q1
Market factor	0.751	0.802	0.841	0.694	0.783	0.032
	(23.477)**	(25.452)**	(30.941)**	(24.110)**	(39.352)**	(0.929)
SMB	−0.161	0.040	0.047	−0.056	−0.031	0.131
	(2.268)*	(1.369)	(0.736)	(0.990)	(0.406)	(1.113)
HML	0.066	−0.205	−0.287	−0.543	−0.449	−0.515
	(0.858)	(2.698)**	(3.826)**	(7.370)**	(7.331)**	(4.352)**
RMW	−0.032	0.396	0.127	−0.210	−0.200	−0.168
	(0.429)	(6.165)**	(1.831)+	(1.940)+	(2.063)*	(1.114)
CMA	0.088	0.271	−0.059	0.002	−0.080	−0.168
	(0.920)	(2.393)*	(0.653)	(0.012)	(0.667)	(1.059)
Alpha	0.204	0.091	0.621	0.729	0.854	0.650
	(3.297)**	(0.911)	(6.497)**	(4.751)**	(4.463)**	(3.556)**
Number of periods	408	408	408	408	408	408

Table B.9. Explaining the Industry Dispersion Anomaly During Normal and Displacement Periods Using the World Fama-French Five Factor Model

This table presents results for time-series portfolio regressions. For each regression, Newey and West (1987) standard errors with optimal lag selection are estimated with absolute *t*-statistics reported in parentheses. +, *, ** denote statistical significance at the 10%, 5% and 1% levels. The sample period is from July 1990 to June 2024. The variable definitions [descriptions] are presented in Table 3 [Table A.1].

	IDISP Portfolio	Q5 – Q1
Market factor	0.009	0.044
	(0.225)	(0.568)
SMB	0.195	−0.078
	(1.835)+	(0.513)
HML	−0.470	−1.262
	(4.363)**	(4.832)**
RMW	−0.135	−0.279
	(1.159)	(0.682)
CMA	−0.198	−0.231
	(1.390)	(0.721)
Alpha	0.666	0.555
	(3.702)**	(1.913)+
Period type	Normal	Displacement
Number of periods	365	43

Table B.10. A Ricardian Model of International Asset Pricing: Performance Tests Using the World Fama-French Five Factor Model

This table presents results for asset pricing tests using a generalized method of moments (GMM) procedure with optimal weights. The test assets are 20 economy-industry portfolios. For developed markets only, the sample period is from July 1990 to June 2024. The variable definitions [descriptions] are presented in Table 3 [Table A.1]. Summary statistics for the economy-industry portfolios are shown in Table A.2.

Factor	**GMKT**	**SMB**	**HML**	**RMW**	**CMA**		
World Fama-French Five Factor Two-step GMM (Optimal) Estimates						A.R-sq	UHJM
			Developed Markets Only				
Factor price	0.807	0.451	0.976	0.057	0.608	0.064	0.388
	[0.000]**	[0.002]**	[0.000]**	[0.648]	[0.000]**		[0.098]+
SDF loading	0.045	0.099	0.143	0.032	−0.002		
	[0.001]**	[0.021]*	[0.039]*	[0.643]	[0.986]		
Factor	**GMKT**	**SIZE**	**IAROE**	**CRX**			
World Multifactor Two-step GMM (Optimal) Estimates						A.R-sq	UHJM/CHJM
			Developed Markets Only				
Factor price	0.439	0.021	1.535	1.025		0.567	0.390
	[0.000]**	[0.579]	[0.000]**	[0.000]**			[0.169]
SDF loading	−0.028	0.082	0.289	0.057			0.032
	[0.000]**	[0.000]**	[0.000]**	[0.000]**			[0.901]

I estimate Newey and West (1987) standard errors with optimal lag selection. *p*-values are reported in brackets. UHJM and CHJM denote the unconditional and conditional Hansen–Jagannathan metrics, respectively, computed as the Hansen–Jagannathan norm of the pricing-error vector evaluated at the optimal GMM estimates. The reported statistics test the null hypothesis that the corresponding pricing-error measure is equal to zero. A.R-sq is the adjusted R-squared from a cross-sectional regression of average excess returns on the mean factor exposure (or beta) estimates. +, *, ** denote statistical significance at the 10%, 5% and 1% levels.

Figure B.6. World CAPM Betas and Fama-French Size-Profitability Portfolios

This figure presents a linear regression fit and a scatter plot for the cross-sectional relation between the mean monthly portfolio return and the average generalized method of moments (GMM) estimate of the exposure (or beta) of the global market factor (GMKT) for the test assets. The test assets are 20 global Fama French portfolios for size and operating profits (with plot markers DVOXY; X represents the size portfolio number and Y represents the profitability portfolio number). The beta estimates are derived from a single-factor, or world CAPM, specification. The sample period is from July 1990 to June 2024. The variable definitions [descriptions] are presented in Table 3 [Table A.1].

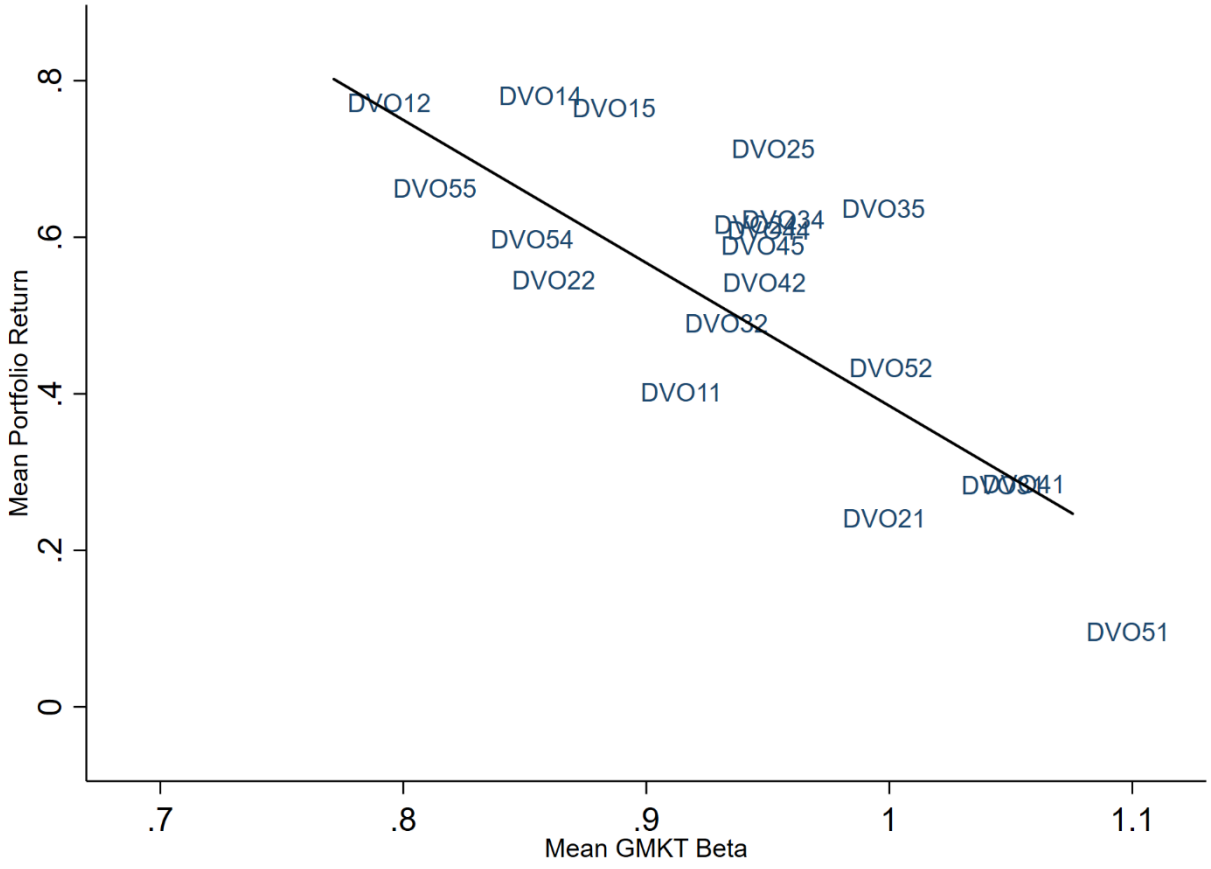


Table B.11. A Ricardian Model of International Asset Pricing: Performance Tests Using Global Fama-French Portfolios

This table presents results for asset pricing tests using a generalized method of moments (GMM) procedure with optimal weights. 20 global Fama-French portfolios are used for each test. For developed markets only, the sample period is from July 1990 to June 2024. The variable definitions [descriptions] are presented in Table 3 [Table A.1].

Panel A

Factor	**GMKT**	**SIZE**	**IAROE**	**CRX**			
20 Portfolios Formed on Size and Operating Profitability					A.R-sq	Hansen J	UHJM/CHJM
World CAPM Two-step GMM (Optimal) Estimates							
Factor price	0.532				0.569		0.519
	[0.000]**						[0.091]+
SDF loading	0.025						
	[0.000]**						
World Multifactor Two-step GMM (Optimal) Estimates							
Factor Price	0.900	1.107	1.007	8.255	0.800	36.287	0.794
	[0.000]**	[0.000]**	[0.000]**	[0.000]**		[1.000]	[0.995]
SDF Loading	0.089	0.085	0.225	0.514			0.705
	[0.000]**	[0.000]**	[0.000]**	[0.000]**			[0.469]
20 Portfolios Formed on Size and Investment					A.R-sq	Hansen J	UHJM/CHJM
World CAPM Two-step GMM (Optimal) Estimates							
Factor price	0.564				0.638		0.594
	[0.000]**						[0.105]
SDF loading	0.026						
	[0.000]**						
World Multifactor Two-step GMM (Optimal) Estimates							
Factor price	0.780	−0.076	2.294	0.563	0.698	23.019	1.274
	[0.000]**	[0.110]	[0.000]**	[0.000]**		[1.000]	[0.976]
SDF loading	0.120	0.131	0.477	0.017			1.010
	[0.000]**	[0.000]**	[0.000]**	[0.069]+			[0.529]

I estimate Newey and West (1987) standard errors with optimal lag selection. *p*-values are reported in brackets. UHJM and CHJM denote the unconditional and conditional Hansen–Jagannathan metrics, respectively, computed as the Hansen–Jagannathan norm of the pricing-error vector evaluated at the optimal GMM estimates. The reported statistics test the null hypothesis that the corresponding pricing-error measure is equal to zero. Hansen J denotes the Hansen (1982) J statistic for the null hypothesis that the overidentifying restrictions are valid. A.R-sq is the adjusted R-squared from a cross-sectional regression of average excess returns on the mean factor exposure (or beta) estimates. +, *, ** denote statistical significance at the 10%, 5% and 1% levels.

Panel B

Factor	GMKT	SIZE	IAROE	CRX			
20 Portfolios Formed on Size and Book-to-Market					A.R-sq	Hansen J	UHJM/CHJM
World CAPM Two-step GMM (Optimal) Estimates							
Factor price	0.473				0.198		0.594
	[0.001]**						[0.120]
SDF loading	0.022						
	[0.001]**						
World Multifactor Two-step GMM (Optimal) Estimates							
Factor price	0.700	0.980	0.060	7.900	0.651	15.316	0.440
	[0.000]**	[0.000]**	[0.312]	[0.000]**		[1.000]	[0.983]
SDF loading	0.042	0.130	0.010	0.485			0.283
	[0.000]**	[0.000]**	[0.330]	[0.000]**			[0.515]
20 Portfolios Formed on Size and Momentum					A.R-sq	Hansen J	UHJM/CHJM
World CAPM Two-step GMM (Optimal) Estimates							
Factor price	0.566				0.504		0.655
	[0.000]**						[0.092]+
SDF loading	0.027						
	[0.000]**						
World Multifactor Two-step GMM (Optimal) Estimates							
Factor price	0.346	1.172	1.170	2.672	0.799	15.139	0.978
	[0.000]**	[0.000]**	[0.000]**	[0.000]**		[1.000]	[0.866]
SDF loading	0.071	0.241	0.294	0.155			0.678
	[0.000]**	[0.000]**	[0.000]**	[0.000]**			[0.478]

I estimate Newey and West (1987) standard errors with optimal lag selection. *p*-values are reported in brackets. UHJM and CHJM denote the unconditional and conditional Hansen–Jagannathan metrics, respectively, computed as the Hansen–Jagannathan norm of the pricing-error vector evaluated at the optimal GMM estimates. The reported statistics test the null hypothesis that the corresponding pricing-error measure is equal to zero. Hansen J denotes the Hansen (1982) J statistic for the null hypothesis that the overidentifying restrictions are valid. A.R-sq is the adjusted R-squared from a cross-sectional regression of average excess returns on the mean factor exposure (or beta) estimates. +, *, ** denote statistical significance at the 10%, 5% and 1% levels.

Figure B.7. Industry-Adjusted Return on Equity (IAROE) Betas and Fama-French Size-Profitability Portfolios

This figure presents a linear regression fit and a scatter plot for the cross-sectional relation between the mean monthly portfolio return and the average generalized method of moments (GMM) estimate of the exposure (or beta) of the industry-adjusted return on equity factor (IAROE) for the test assets. The test assets are 20 global Fama French portfolios for size and operating profits (with plot markers DVOXY; X represents the size portfolio number and Y represents the profitability portfolio number). The beta estimates are derived from a world multifactor specification. The sample period is from July 1990 to June 2024. The variable definitions [descriptions] are presented in Table 3 [Table A.1].

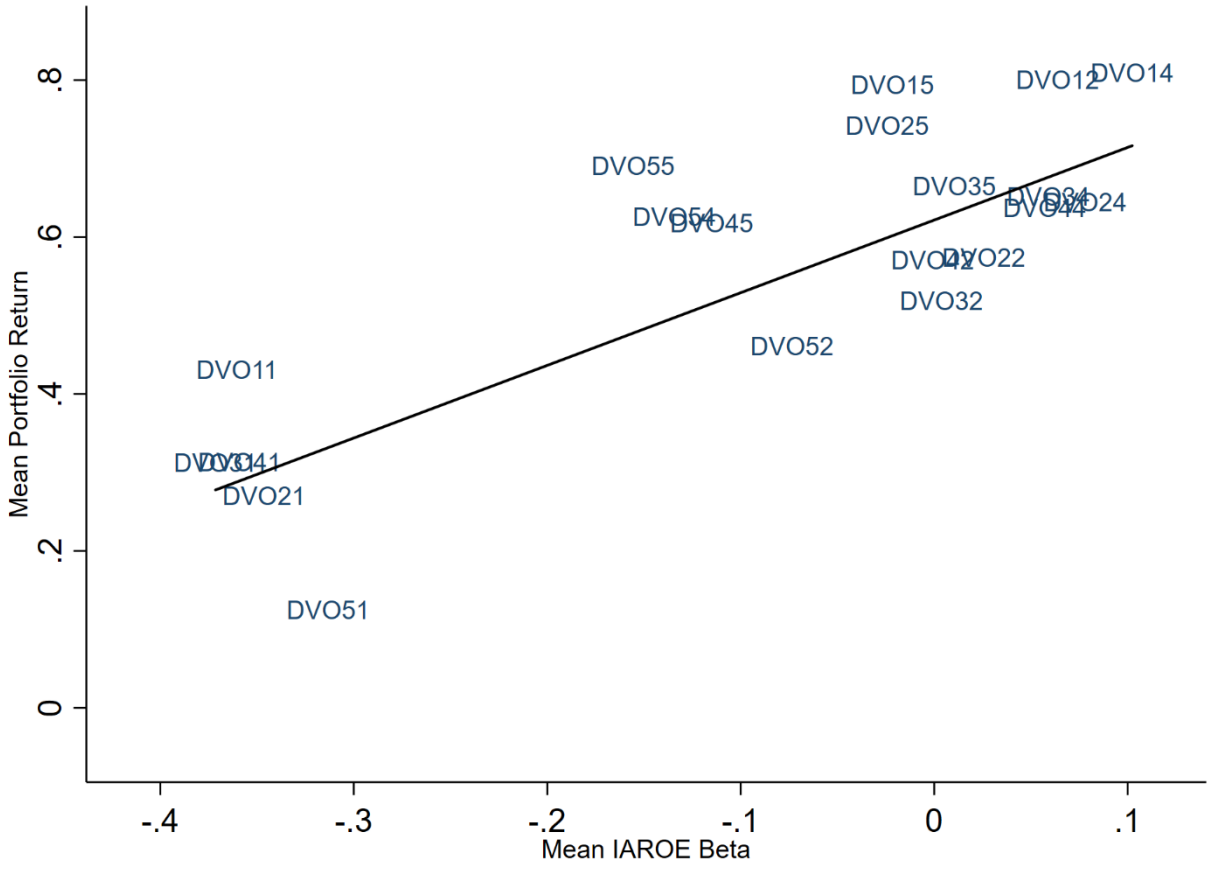


Figure B.8. Industry-Adjusted Return on Equity (IAROE) Betas and Fama-French Size-Investment Portfolios

This figure presents a linear regression fit and a scatter plot for the cross-sectional relation between the mean monthly portfolio return and the average generalized method of moments (GMM) estimate of the exposure (or beta) of the industry-adjusted return on equity factor (IAROE) for the test assets. The test assets are 20 global Fama French portfolios for size and investment (with plot markers DVOXY; X represents the size portfolio number and Y represents the investment portfolio number). The beta estimates are derived from a world multifactor specification. The sample period is from July 1990 to June 2024. The variable definitions [descriptions] are presented in Table 3 [Table A.1].

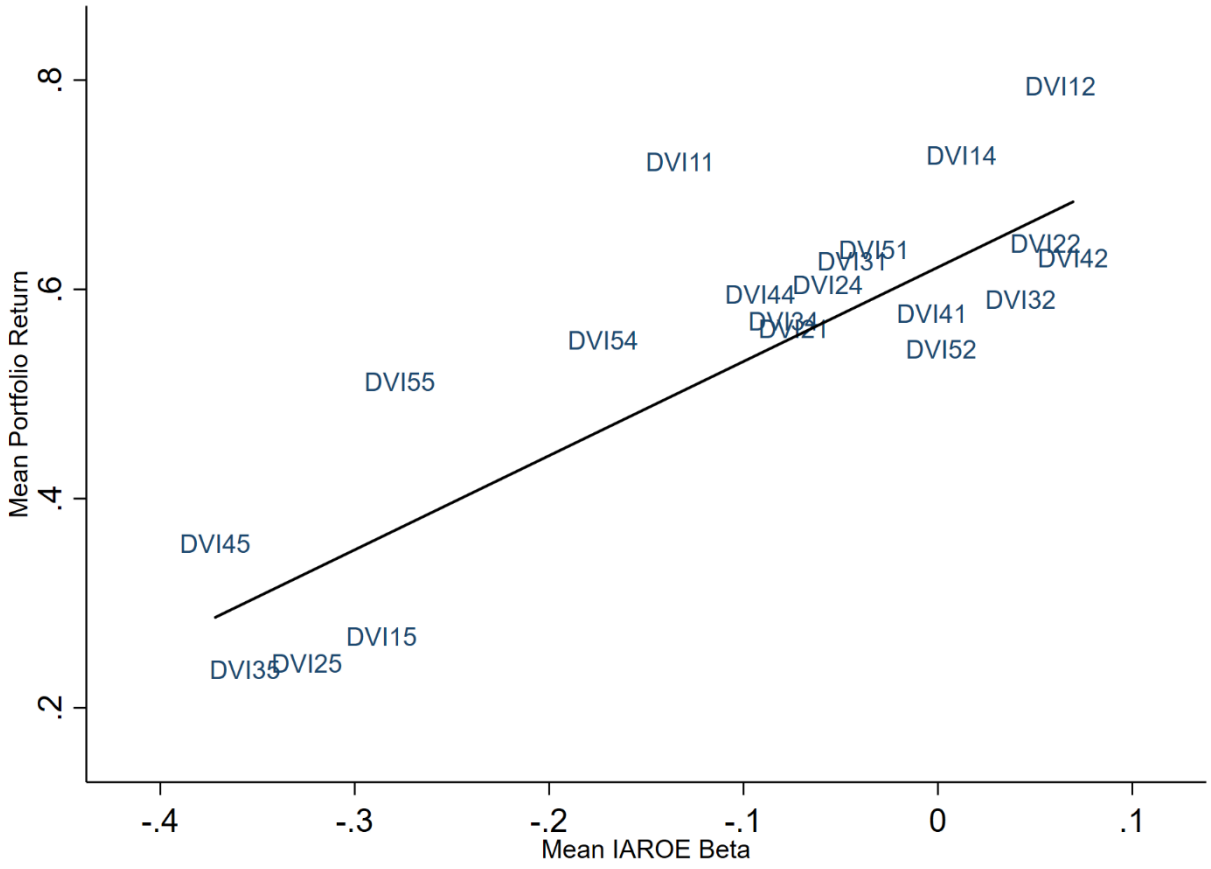


Table B.12. Placebo Conditioning Instruments and Conditional Pricing Errors

This table presents results for asset pricing tests using a generalized method of moments (GMM) procedure with optimal weights. The test assets are 20 economy-industry portfolios. For developed markets only, the sample period is from July 1989 to June 2024. The variable definitions [descriptions] are presented in Table 3 [Table A.1]. Summary statistics for the economy-industry portfolios are shown in Table A.2.

Factor	**GMKT**	**SIZE**	**IAROE**	**CRX**			
World Multifactor Two-step GMM (Optimal) Estimates					A.R-sq	Hansen J	UHJM/CHJM
Developed Markets Only (AR Placebo Instrument Set)							
Factor price	0.501	0.917	0.609	0.169	0.092	15.705	0.487
	[0.000]**	[0.000]**	[0.000]**	[0.050]+		[1.000]	[0.167]
SDF loading	0.066	0.166	0.191	0.007			0.411
	[0.000]**	[0.000]**	[0.000]**	[0.218]			[0.352]
Developed Markets Only (VAR Placebo Instrument Set)							
Factor price	0.799	0.120	0.316	0.966	-0.150	15.672	0.332
	[0.000]**	[0.579]	[0.000]**	[0.000]**		[1.000]	[0.036]
SDF loading	0.058	0.050	0.103	0.063			0.277
	[0.000]**	[0.000]**	[0.000]**	[0.000]**			[0.353]

I estimate Newey and West (1987) standard errors with optimal lag selection. *p*-values are reported in brackets. UHJM and CHJM denote the unconditional and conditional Hansen–Jagannathan metrics, respectively, computed as the Hansen–Jagannathan norm of the pricing-error vector evaluated at the optimal GMM estimates. The reported statistics test the null hypothesis that the corresponding pricing-error measure is equal to zero. Hansen J denotes the Hansen (1982) J statistic for the null hypothesis that the overidentifying restrictions are valid. A.R-sq is the adjusted R-squared from a cross-sectional regression of average excess returns on the mean factor exposure (or beta) estimates. +, *, ** denote statistical significance at the 10%, 5% and 1% levels.

Appendix C

C.1 Economies and Firms Under Imperfect Competition

Consider a Ricardian model with three dates t = 0, 1, 2. In the initial transactional period (t = 0), financial market completeness allows for trade in a complete set of Arrow-Debreu claims.[i] In the following trading period (t = 1), imperfect competition between firms determines prices for goods, similar to the BEJK approach.

There are N economies where each economy at time t = 1 produces a continuum of sectoral goods indexed by $j \in [0,1]$. The input cost in economy i at time t = 1 is $c_{i,1}$. A firm k can convert one bundle of inputs into a quantity $z_{ki,1}(j)$ of good j at constant returns to scale, and the measurable function $j \to z_{ki,1}(j)$ is the sole driver of heterogeneity in production technology across firms. Formally, the efficiency of producing good j is the draw (independent for each j) of a random variable from probability distribution $F_{ki,t}(z) = \Pr[Z_{ki,t} \leq z]$. I assume an extreme-value Fréchet distribution for efficiency of firm k in economy i at time t.

[C1] $$F_{ki,t}(z) = e^{-T_i z^{-\theta}}$$

In [C1], the economy's time-invariant state of technology $T_i > 0$ (reflecting its absolute advantage), and the global (i.e., economy-time-invariant) prevalence of comparative advantage in international trade $\theta > 0$. Here, a larger T_i represents a greater probability of an elevated level of efficiency, while a larger θ represents less variability in efficiency.

Assuming the maximiser is unique for almost every j, a measurable map $\xi_i: [0,1] \to \Psi_i, k_i(j) = \xi_i(j), \Psi_i \coloneqq [0,1]$, injective almost everywhere (a.e.), assigns each good to its most efficient domestic firm, and no firm produces more than one good. Under constant returns to scale,

[i] See fn. 9.

the cost of producing a unit of good j in economy i at time t = 1 is $c_{i,1}/z_{ki,1}(j)$. There is also a time-invariant "iceberg" trade cost $d_{ni} > 1$ associated with exporting a unit of good j from economy i to economy n $(\neq i)$.[ii] The total cost of producing and exporting a unit of good j from economy i to economy n at time t = 1 for firm k is $h_{kni,1}(j)$.

[C2] $$h_{kni,1}(j) = \left(\frac{c_{i,1}}{z_{ki,1}(j)}\right) d_{ni}$$

Like BEJK, I assume imperfect (Bertrand) competition in which markups vary across firms to generate variation in measured productivity. I also assume that consumers are log-utility maximizers. Buyers in destination economy n are presented with a choice of firms that can be ranked based on their total cost of delivering a unit of good j, $h_{kni,1}(j)$. After ranking these costs in ascending order, $h_n^{(1)}(j) \leq h_n^{(2)}(j) \leq \cdots \leq h_n^{(N)}(j)$, the destination market is eventually supplied by the lowest-cost firm with a price set to the second order statistic of the vector of total costs.

[C3] $$p_{n,1}(j) = h_n^{(2)}(j)$$

Given that buyers in destination economy n eventually pay the second lowest cost of the cost vector presented by the source economies, the price distribution for goods traded in economy n at time t =1 is $G_{n,1}^{(2)}(p)$ with the corresponding parameter, $\Phi_{n,1}$.

[C4] $$G_{n,1}^{(2)}(p) = 1 - e^{-\Phi_{n,1}p^{\theta}}\left[\sum_{i=1}^{N} e^{\left[T_i\left(c_{i,1}d_{ni}\right)^{-\theta}\right]p^{\theta}} - (N-1)\right]$$

[C5] $$\Phi_{n,1} = \sum_{i=1}^{N} T_i\left(c_{i,1}d_{ni}\right)^{-\theta}$$

C.2 Solving for Equilibrium Consumption Under the Eaton-Kortum Framework

In addition to the prices that emerge due to imperfect competition between firms, trade shares and

[ii] Note that $d_{ii} = 1$; and for any three economies i, n, and k, $d_{ni} \leq d_{nk}d_{ki}$ (i.e., the triangle inequality of cross-border arbitrage).

consumption are achieved within the probabilistic EK equilibrium at time $t = 1$.

C.2.1. *Trade Shares as the Foundation of the Probabilistic Approach for Aggregate Measures*

Economy i's share of exports to economy n at time $t = 1$, $X_{ni,1}/X_{n,1}$, is equal to the probability that economy i sells a good j to economy n at time $t = 1$, $\pi_{ni,1}$.

[C6] $$\pi_{ni,1} = \frac{T_i(c_{i,1}d_{ni})^{-\theta}}{\Phi_{n,1}} = \frac{X_{ni,1}}{X_{n,1}}$$

Here at time $t = 1$; $X_{n,1}$ is the total spending in economy n, with $X_{ni,1}$ being spent on goods imported from economy i, and $X_{nn,1}$ being spent on goods produced domestically in economy n. [C6] provides a foundation for the probabilistic competitive equilibrium concept in the EK model, a competitive equilibrium that engenders optimal consumption and spending at the economy level.

C.2.2. *Aggregate Demand and Consumption Under the Probabilistic Approach*

The demand from log-utility consumers in economy n is determined by the following utility maximization exercise.

[C7] $$\max_{Q_{n,1}(j)} U = \int_0^1 \ln Q_{n,1}(j)dj$$

s.t. $$\int_0^1 p_{n,1}(j)Q_{n,1}(j)dj = X_{n,1}$$

For this exercise, the Lagrangian in [C8] can be used to solve for the optimal consumption of good j economy n at time $t = 1$, $Q^*_{n,1}(j)$.

[C8] $$\mathcal{L} = \int_0^1 \ln Q_{n,1}(j)dj - \omega\left(\int_0^1 p_{n,1}(j)Q_{n,1}(j)dj - X_{n,1}\right)$$

[C9] $$Q^*_{n,1}(j) = \frac{X_{n,1}}{p_{n,1}(j)}$$

Consumers aggregate over all goods and attach an aggregate price $p_{n,1}$ to their spending. The total consumption in economy n at time $t = 1$ is $C_{n,1}$.

[C10] $$C_{n,1} = \int_0^1 \frac{X_{n,1}}{p_{n,1}(j)}dj$$

[C11] $$C^*_{n,1} = \frac{X_{n,1}}{p_{n,1}}, \text{ where } p_{n,1} = \gamma \Phi_n^{-1/\theta} \text{ and } \gamma = e^{\psi(\theta)}$$

In [C11], the optimal aggregate consumption is determined by import spending, $X_{n,1}$, the price index $\Phi_{n,1}$, and the demand elasticity γ. The demand elasticity γ is influenced by θ (the global prevalence of comparative advantage in international trade).[iii]

C.2.3. *The Labor Market and the Goods Market Under the Probabilistic Approach*

The labor market assumption is a key consideration in determining a competitive equilibrium. EK discuss two alternatives: mobile labor and immobile labor. In the mobile labor case, workers can freely move between manufacturing and non-manufacturing sectors while wages are set exogenously by the non-manufacturing sector. In the immobile labor case, the number of manufacturing workers is fixed, and the manufacturing sector cannot employ additional workers in the presence of increasing demand.

To explore the role of trade shocks in currency risk premia, this paper uses the mobile labor assumption which takes an economy's wage $w_{i,1}$, manufacturing share α, and income $Y_{i,1}$ as exogenous. Therefore, the manufacturing labor allocation $L_{i,1}$ is a choice variable with a nonbinding labor constraint.

[C12] $$w_{i,1}L_{i,1} = \beta_p \sum_{n=1}^{N} \pi_{ni,1} X_{n,1} \leq Y_{i,1}$$

[C13] $$X_{n,1} = \frac{1-\beta_p}{\beta_p} w_{n,1}L_{n,1} + \alpha Y_{n,1}$$

Given an exogenous wage w_i, the input cost in economy i at time $t = 1$ can be recast as follows.

[C14] $$c_{i,1} = w_{i,1}^{\beta_p} p_{i,1}^{1-\beta_p}$$

In [C14], the input cost is determined by wages and prices ($w_{i,1}$, $p_{i,1}$), along with the extent to

[iii] As θ declines with a stronger force of comparative advantage, the digamma function $\psi(\theta)$ implies that consumers become more responsive to prices.

which goods are used as intermediate inputs in production, $1 - \beta_p$. The aggregate price $p_{i,1}$ itself can be represented as a function of wages and prices in partner economies.

[C15] $$p_{i,1} = \gamma \left[\sum_{n=1}^{N} T_n \left(d_{in} w_n^{\beta_p} p_{n,1}^{1-\beta_p}\right)^{-\theta}\right]^{-1/\theta}$$

The total export sales $S_{i,1}$ from economy i at time t = 1 must be balanced by imports $X_{ni,1}$ in partner economies while the total imports $X_{i,1}$ to economy i at time t = 1 must be balanced by exports $X_{in,1}$ from partner economies.

[C16] $$S_{i,1} = \sum_{n=1}^{N} X_{ni,1} = T_i \left(w_{i,1}^{\beta_p} p_{i,1}^{1-\beta_p}\right)^{-\theta} \sum_{n=1}^{N} \left(d_{ni}^{-\theta} X_{n,1} / \Phi_{n,1}\right)$$

[C17] $$X_{i,1} = \sum_{n=1}^{N} X_{in,1}$$

C.2.4. *Competitive Equilibria Within Ricardian Trade Under the Probabilistic Approach*

In a competitive equilibrium, a representative consumer maximizes aggregate consumption subject to a budget constraint (see Section C.2.2) while firms operate in an environment with perfect competition where prices are determined as described in Section C.1. In this competitive equilibrium, market clearing conditions (see Section C.2.3) are applied to the international goods market and the labor market.

In an environment with complete financial markets, a social planner can utilize Pareto weights to achieve the competitive equilibrium (Negishi, 1960). Moreover, lump sum transfers can be made during the initial transactional period so that the Pareto weights are unitary. In the presence of trade shocks, the social planner's problem is static under certain separability conditions for each shock realization. Hence the social planner's objective is as follows:

[C18] $$\max_{X_{ni,t}\ L_{i,t}} \sum_{\mathrm{i}=1}^{\mathrm{N}} \left(\ln\left(C_{\mathrm{i},1}\right) + \beta_c E\left[\ln\left(C_{\mathrm{i},2}\right)\right]\right)$$

s.t. $$\sum_{n=1}^{N} X_{ni,t} = T_i \left(c_{i,t}\right)^{-\theta} \sum_{n=1}^{N} \left(d_{ni}^{-\theta} \left[\frac{1-\beta_p}{\beta_p} w_{n,t} L_{n,t} + \alpha Y_{n,t}\right] / \Phi_{n,t}\right)$$

$$L_{i,t} \leq Y_{i,t}/w_{i,t} \qquad \forall i,t$$

The problem in [C18] can be solved using a Lagrangian with multipliers $\mu_{i,t}^{X}$ and $\mu_{i,t}^{L}$ for clearing conditions in the goods market and labor market, respectively. The first order conditions produce the following equations for the multipliers.

[C19] $$\mu_{i,t}^{X} = \frac{1}{p_{i,t}C_{i,t}} = \frac{1}{X_{i,t}}$$

[C20] $$\mu_{i,t}^{L} = \left(\frac{1-\beta_p}{\beta_p} \cdot \frac{w_{i,t}}{\Phi_{i,t}}\right) \sum_{n=1}^{N} \mu_{n,t}^{X} T_n \left(c_{n,t} d_{in}\right)^{-\theta}$$

The first order conditions together with the goods market clearing conditions produce the optimal value for import spending, and therefore the optimal value of consumption.

[C21] $$X_{i,t}^{*} = 2\alpha \sum_{n=1}^{N} \pi_{ni,t} Y_{n,t}$$

[C22] $$C_{i,t}^{*} = 2\alpha\gamma^{-1}\Phi_{i,t}^{1/\theta} \sum_{n=1}^{N} \pi_{ni,t} Y_{n,t}$$

C.3 Market Size and Explicit Firm-Level Profits in the Benchmark Period

EK use a probabilistic approach to determine trade shares, thus shaping aggregate outcomes such as $X_{i,t}^{*}$ and $C_{i,t}^{*}$. However, in order to study the implications for international stock returns, it is important to characterize the explicit equilibrium for firm-level profits. Rather than rely on [C21] through the use of probabilistic trade shares, I define the total market available for a firm. For destination economy n, the total available spending is $X_{n,t}^{M}$, with superscript M representing the total available market.

[C23] $$X_{n,t}^{M} = 2\alpha Y_{n,t}$$

Upon determining [C23], the total available spending in economy n, firm-level outcomes can be derived by acknowledging markups. As the equilibrium low-cost supplier of good j to economy n at time t = 1, firm k applies the following markup.

[C24] $$U_{kn,1} = \frac{h_n^{(2)}(j)}{h_n^{(1)}(j)}$$

Under log utility, total available spending $X_{n,1}^M$ is spread uniformly across the continuum of goods. Let $\varpi_{n,1}(j)$ represent revenue density (revenue per unit of goods measure). Hence,

[C25] $$\int_0^1 \varpi_{n,1}(j)\, dj = X_{n,1}^M$$

A convenient discrete intuition is to partition the interval into J equal segments; each good j then receives $X_{n,1}^M/J$ of spending. Under the discrete representation, the revenue firm k earns for supplying any good j to economy n at time t = 1, $x_{kn,1}$, depends on the size of the market for the good.

[C26] $$x_{kn,1} = \frac{X_{n,1}^M}{J}$$

Under the defined markup in [C24], the total production cost for firm k in economy n at time t = 1, $V_{kn,1}$ is [C27].

[C27] $$V_{kn,1} = \frac{x_{kn,1}}{U_{kn,1}}$$

Let $\Lambda_{ki,1}$ be the set of served markets for firm k from economy i at time t = 1. Hence the total profits for firm k at time t = 1, $\Pi_{ki,1}$ is [C28].

[C28] $$\Pi_{ki,1} = \sum_{n \in \Lambda_{ki,1}} x_{kn,1} - V_{kn,1}$$

C.4 Using Simulated Method of Moments to Identify Parameters for Generating Stock Returns

This section describes the simulated method of moments (SMM) approach used to estimate the model parameters that govern the mapping from competitive shocks to stock returns in [7]. An important methodological point concerns the relationship between the model's scope and the matching targets. The model generates outcomes for the full universe of competing firms, including those that would experience extreme displacement and potentially exit. However, the

SMM procedure targets conditional moments computed from publicly listed firms (Bessembinder et al., 2023). This is the population relevant for asset pricing.

This represents standard conditional calibration in structural estimation (Gourieroux and Monfort, 1996): the model is structurally general, but the moment conditions are conditional on the publicly traded subsample. The estimated parameters should be interpreted as those governing competitive dynamics among firms that remain publicly traded, rather than as parameters describing entry, exit, or private-firm behavior. Because the model's scope is broader than the empirical population, it naturally generates greater dispersion in outcomes than observed in public-firm data. The SMM procedure disciplines the model to match conditional distributional moments of listed firms rather than unconditional moments of the full firm universe. This approach is appropriate by design: the model's comprehensive scope captures realistic displacement dynamics, while the matching targets reflect the asset-pricing environment of public securities. Given that the empirical analysis in this paper concerns publicly listed securities, the estimated parameters are intended to characterize competitive dynamics within that population; representativeness with respect to unlisted firms is not required for identification or interpretation.

Equations [1] and [2] along with [5] to [7] present a careful treatment of the transition from trade shocks to stock returns conditional on the parameter for cost stickiness ϱ, and the parameter for the dividend-profit ratio, δ. To align the scale for output volatility κ across supply-side shocks and demand-side shocks, I introduce the following convention with two additional parameters for the relative weights on supply and demand shocks, ω_S and ω_D.

[C29] $$\mathrm{K} = \frac{2\kappa}{\omega_S + \omega_D}$$

Given that K effectively distributes the scale for output volatility using the average value of ω_S and ω_D, the respective scaling factors for supply-side shocks and demand-side shocks are

determined in the following manner.

[C30] $$\kappa_s = \mathrm{K}\omega_S$$

$$\kappa_d = \mathrm{K}\omega_D$$

In order to identify the necessary parameters for generating stock returns (ϱ , δ, ω_S, ω_D) within this paper's model, I employ a simulated method of moments (SMM) approach (McFadden, 1989; Pakes and Pollard, 1989), which matches simulated moments from the model to their empirical counterparts. The SMM approach requires selecting a set of moment conditions that characterize the distribution of global stock returns and specifying a weighting matrix that determines the relative importance of each moment condition in the objective function (Duffie and Singleton, 1993; Gourieroux and Monfort, 1996). This paper presents results using a two-step procedure: the first step employs an identity weighting matrix, while the second step uses an asymptotically optimal weighting matrix constructed from the variance-covariance matrix of the moment conditions (Hansen, 1982). The moment conditions target four key distributional characteristics of (annual) stock returns in developed markets as documented by Bessembinder et al. (2023): the mean (0.1402), standard deviation (0.889), median (0.0244), and skewness (19.922).

Each SMM exercise is implemented as one trial for the scenario of simultaneous demand-side and supply-side shocks. I use the following simulation algorithm to generate the benchmark for time t = 1: First, I use parameters and macroeconomic values from EK and Brown (2024) to simulate economy-level characteristics that are consistent with a global environment of strong comparative advantage (θ = 3.60). Each simulation trial consists of 30 economies. The main economy-level characteristics are the state of technology T_i, trade openness d_n, total income $Y_{i,1}$, and the cost level $c_{i,1}$. The parameters and characteristic moments are presented in Panel A of Table 1.

Second, I use the simulated economy-level characteristics to generate random values of efficiency for 500 possible firms in each economy using an extreme-value Fréchet distribution, $F_{ki,t}(z) = e^{-T_i z^{-\theta}}$. Each firm attempts to satisfy global markets for a single good. There are 15,000 different economy-goods markets (i.e., 30 simulated economies with 500 goods for each economy). Equation [C23] shows that for economy i at time t = 1, the total available spending $X_{n,1}^{M}$ (in equilibrium) is $2\alpha Y_{n,t}$. Therefore, each supplying firm for economy n at time t = 1 earns $x_{kn,1} = 2\alpha Y_{n,t}/500$ under the log utility assumption.

Third, "iceberg" trade costs (in logs) d_{ni} are generated using a beta distribution with the scale parameter as the simulated $\ln(d_n)$, and a shape parameter of 2. Fourth, for each destination economy-goods market, total production and delivery costs, $h_{kni,1}(j) = c_{ki,1}d_{ni}$ are ranked to determine the supplying firm and its destination markup, $U_{kn,1}$. From there, the total profits $\Pi_{ki,1}$ are determined for each firm using [5] with $V_{kn,1} = x_{kn,1}/U_{kn,1}$. Table C.1 shows that across all five trials, there is a total of 6,774 simulated operating firms time t = 1 with an average of roughly 1,355 firms per trial.

Within a given SMM exercise, each objective evaluation produces 100 different possible outcome profiles for the final period (t = 2). In this period, each *operating* firm experiences stochastic shocks consistent with [1] to [3]. For each operating firm, $c_{ki,2}$ and $x_{kn,2}$ are directly impacted by these shocks as described in [5] and [6], which engender a new equilibrium of profits $\Pi_{ki,2}$ and a stock return $R_{ki,2}$ as described in [7]. The SMM exercise identifies parameters (ϱ , δ, ω_S, ω_D) which produce the stock return moments that best match the target moments.

In Table C.1, Panel A presents the results of the SMM exercise for five trials. Each trial has its own (scaled) optimal weighting matrix. I average the matrix values element by element to show the average (scaled) optimal weighting matrix. The model generates a more complete

distribution than observed in public markets due to the population difference between the model's scope and the empirical targets. Accordingly, the optimal weighting matrix reflects the tradeoffs inherent in matching conditional moments: the calibration prioritizes matching the mean of global stock returns (i.e., weight equal to 2.820) over the standard deviation (0.964), with the negative interaction term (−1.303) indicating these objectives compete when targeting moments from publicly listed firms rather than unconditional moments of the full firm universe. The model balances these objectives by reproducing the magnitude of mean returns while accepting that dispersion reflects the broader population underlying the simulations.

The model performs well for its intended purpose of mapping simulated profits into realistic stock returns among publicly listed firms. Panel A shows the results of a Monte-Carlo replication exercise (using 250 replications across the five trials), where the posterior-predictive p-value is greater than 0.10 for each moment. Hence, the model does not reject the null hypothesis that each target moment was generated from the model's empirical distribution. Moreover, the global Bonferroni-adjusted p-value and the global Simes p-value (for a joint test of whether all four moments can be derived from the replication distribution) are 1.000 and 0.968 respectively.

In Table C.1, Panel B shows the identified parameters for each trial. In every case, the relative weight of demand-side shocks ω_D is greater than the relative weight of supply-side shocks ω_S. Demand-side shocks reproduce symmetry in the return distribution, while supply-side shocks reproduce the observed skewness and dispersion of global stock returns. The relative importance of demand-side shocks is a direct reflection of the relative importance of symmetry in the return distribution.

C.5 Stochastic Discount Factor (SDF) Proxies Within Ricardian Trade

By using the identified parameters to generate equity returns, the model also allows for the

reproduction of local and global market factors. To characterize the pricing patterns that emerge in expected excess equity returns, this paper explores two proxies for the stochastic discount factor (SDF): the global market factor from the world capital asset pricing model (CAPM), and global consumption growth from the world consumption capital asset pricing model (CCAPM).

C.5.1. *The Global Market Factor*

The foundation of the global market factor is the value-weighted global stock return. In the model, the weights correspond to firm size at time $t = 1$.

[C31] $$\mathrm{w}_{ki} = \frac{\sum_{n\in\Lambda_{ki,1}} x_{kn,1}}{\sum_k \sum_{n\in\Lambda_{ki,1}} x_{kn,1}}$$

The weights are then applied to the stock returns at time $t = 2$.

[C32] $$R_2^G = \sum_k \mathrm{w}_{ki}\mathrm{R}_{ki,2}$$

The risk-free rate R_2^f, is then subtracted from the value-weighted global stock return to produce the excess return as the global market factor at time $t = 2$.

[C33] $$RX_2^G = R_2^G - R_2^f$$

C.5.2. *Global Consumption Growth*

The SDF proxy for the CCAPM is global consumption growth at time $t = 2$. The derivation in Equation [C22] shows the probabilistic equilibrium consumption in economy i at time t, $C_{i,t}^*$, where α is the manufacturing share, γ is the demand elasticity, $\Phi_{i,t}$ is the aggregate price index in economy i at time t, and $Y_{n,t}$ is the endowment income in economy n at time t. The probability that economy i sells a good j to economy n at time t is $\pi_{ni,t}$. $\pi_{ni,t}$ is a measure of export diversification in that a larger $\pi_{ni,t}$ corresponds to economy i exporting a wider range of goods to economy n at time t. Global consumption at time t, is simply the sum of equilibrium consumption over all economies.

[C34] $$C^*_{G,t} = \sum_{i=1}^{N} C^*_{i,t}$$

Although consumption is characterized at the economy level, this paper's explicit approach does allow for the Ricardian model to characterize consumption growth in the presence of trade shocks to firms. At time $t = 1$, $C^*_{i,1}$ can be characterized using the probabilistic equilibrium formula in [C22] because economy-level variables such as $c_{i,1}$ are random draws from the assumptions shown in Table 1. However at time $t = 2$, exporter costs are shocked at the firm level and the available market size is shocked at the destination market level; $c_{ki,2} = c_{ki,1}{}^{\varrho}\left(H^s_{ki,t} c_{ki,1}\right)^{1-\varrho}$ and $x_{kn,t} = H^d_{kn,t} x_{kn,1}$. To recover aggregate consumption at time $t = 2$, I first apply a method-of-moments estimator that uses the distribution of firm-level costs in economy i, $c_{ki,2}$, to produce an estimate for costs at the economy level, $\hat{c}_{i,2}$.[iv]

[C35] $$\hat{c}_{i,2} = \left[\frac{1}{K_i}\sum_{k=1}^{K_i} T_i\, c^{\theta}_{ki,t}\right]^{1/\theta}$$

In [C35], K_i represents the total number of firms in economy i. The income in economy n at time $t = 2$, $Y_{n,2}$, can be generated using the sum of the potential revenue amounts for all firms that operate in economy n at time $t = 1$.[v]

[C36] $$Y_{n,2} = \frac{\sum_{k=1}^{K_n} x^p_{kn,2}}{2\alpha}$$

Equations [C35] and [C36] can now be used to characterize $C^*_{i,2}$ with the probabilistic equilibrium formula in [C22]. Using [C34], the gross growth rate of global consumption is $C^*_{G,2}/C^*_{G,1}$.

[iv] A key fact about this Weibull distribution is that its θth moment is $E\left[c_{ki,t}\right] = \left(\frac{c_{i,t}}{T_i^{1/\theta}}\right)^{\theta}\Gamma(1+\theta) = \frac{c^{\theta}_{i,t}}{T_i}$. In other words, for each observation, $c^{\theta}_{i,t} = T_i E\left[c_{ki,t}\right]$.

[v] In [C36], I distinguish between the potential revenue $x^p_{kn,2}$ and the actual revenue $x_{kn,2}$ for a firm k in economy n at time $t = 2$. A firm that operates at time $t = 1$ may be displaced at time $t = 2$. If the firm is displaced, then it will not earn revenue in that market. However, the market would be satisfied by a new entrant that would earn the same potential revenue.

C.6 Complete Markets and the Pricing of Competitive Displacement

In this section, I explain why systematic competitive displacement commands a risk premium even when aggregate uncertainty is fully spanned. Complete markets allow agents to trade a full set of Arrow–Debreu claims contingent on aggregate states of the world. This assumption pins down the stochastic discount factor (SDF) through optimal risk sharing and allows the analysis to abstract from financial frictions.

Any payoff that covaries systematically with the SDF commands a risk premium. What complete markets determine is how aggregate risk is shared; they do not eliminate pricing of systematic redistribution of payoffs conditional on realized aggregate states. The key distinction is therefore between hedging aggregate state uncertainty and pricing cross-sectional reallocation within states. Aggregate shocks are fully spanned and determine the SDF. By contrast, even conditional on a realized aggregate state, firms' relative competitive positions can shift systematically under imperfect competition. Changes in relative costs, market access, or strategic interactions reallocate markups, market shares, and profits across firms within that state. When this redistribution covaries with the SDF, displacement risk is priced even under complete markets. The relevant risk is not which aggregate state occurs, but how firm values are redistributed within that state.

Displacement risk is systematic rather than idiosyncratic because it operates through common economic structure. Supply-side shocks are important mechanisms that affect firms in correlated ways through product-market competition. When relative costs shift, competitive rankings adjust nonlinearly: vulnerable firms experience concentrated downside risk while dominant firms expand markups and market share. Because such shocks often have global components, large sets of firms move together. China's manufacturing productivity surge in the

2000s illustrates this mechanism, simultaneously expanding global consumption possibilities while eroding the competitive positions of many U.S. and European manufacturers across tradable sectors. Complete markets allow investors to hedge the aggregate consumption consequences of such shocks, but the systematic redistribution of firm values from vulnerable incumbents to more competitive producers covaries with the SDF and therefore remains priced.

The priced object in this environment is systematic competitive displacement (i.e., the covariance between the SDF and redistribution of firm values during reallocation episodes) and not idiosyncratic firm failure. Purely firm-specific shocks are diversifiable and unpriced. By contrast, common shocks interacting with imperfect competition generate correlated redistribution that loads on the SDF. Displacement often coincides with positive global supply-side shocks that expand aggregate production while compressing profits for vulnerable firms; states in which vulnerable firms perform relatively well tend to coincide with weaker global competition and higher marginal utility. This covariance generates a displacement risk premium. A relaxation of complete markets would likely amplify these effects but is not required for the core mechanism, making complete markets an appropriate benchmark.

Table C.1. A Ricardian Model of International Asset Pricing: Simulation Parameters

This table presents the parameters that determine equity returns. There are 5 trials (representing 5 global economic systems). 30 simulated economies are drawn from the distribution of economic characteristics for each trial. Simulated firms arise endogenously as a result of imperfect global competition in 500 different industries at time $t = 1$ (serving 15,000 possible economy-industry markets). Across all trials, there is a total of 6,774 simulated firms with an average of roughly 1,355 firms per trial. Stochastic shocks are generated for each simulated firm to produce 100 outcome profiles at time $t = 2$, resulting in a total of 677,400 numerical simulation outcome profiles under global competition. For each trial, the parameters that determine equity returns from outcome profiles (ϱ, ω_S, ω_D, and δ) are identified using a simulated method of moments (SMM) estimator. Panel A shows the (average) scaled optimal weighting matrix, along with the moment matching performance of the SMM estimator using 50 replications per trial for a total of 250 replications. Panel B presents the estimated equity return generating parameters that apply to the simulation outcome profiles for each trial. The descriptions of the model parameters, macroeconomic characteristics, and model outcomes are presented in Table A.1. The model parameters along with moments for the characteristics of the simulated economies are presented in Table 1.

Panel A

Moments for Equity Return Parameters	Mean	Median	Standard Deviation	Skewness
Scaled Optimal Weighting Matrix (Average)				
Mean	2.820			
Median	−0.474	0.085		
Standard deviation	−1.303	0.210	0.964	
Skewness	0.311	−0.049	−0.239	0.131
Matching Performance (5 Trials; 250 Replications)				
Target values (annual data)	0.140	0.024	0.889	19.922
Average simulated value	0.128	0.027	1.100	20.906
Test statistic (empirical percentile of target)	0.708	0.484	0.300	0.384
Two-sided posterior-predictive *p*-value	0.580	0.968	0.600	0.768
Monte-carlo s.e.	(0.031)	(0.011)	(0.031)	(0.027)
Global Bonferroni *p*-value		1.000		
Global Simes *p*-value		0.968		

For each trial, every moment is standardized before computing the (scaled) optimal weighting matrix after the first step of the two-step simulated method of moments (SMM) estimation exercise. The top panel of the table reports the element-by-element average of the five weighting matrices. For each moment (mean, median, standard deviation, and skewness), the bottom panels of the table present the empirical percentile of the target value among the 250 replications (the test statistic), along with its corresponding *p*-value for the test that a target moment can be derived from the replication distribution. Under the null hypothesis, the test statistic is uniformly distributed on (0, 1). Monte-Carlo standard errors for these *p*-values are also reported. The global Bonferroni-adjusted *p*-value and the global Simes *p*-value are each generated from a joint test of whether all four moments can be derived from the replication distribution.

Panel B

Trial Number	(1)	(2)	(3)	(4)	(5)
ϱ	0.289	0.301	0.450	0.449	0.434
ω_S	0.924	0.951	0.150	1.500	0.212
ω_D	6.472	5.595	0.506	7.488	0.500
δ	0.244	0.332	0.150	0.150	0.150