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Optimal Portfolios for Occupational Funds under Time-Varying Correlations in Bull and Bear Markets*

Assessing the Ex-Post Economic Value

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Abstract

We systematically assess the recursive performance costs—both ex-ante and ex-post—in recursive real time out-of-sample experiments of implementing diversification strategies that allow occupational investment vehicles (OIVs, like pension funds) to allocate wealth across available assets (equities) by taking into account the presence of regimes and non-stationarities (i.e., structural change in parameters) in the correlation between sector-specific earnings/wages dynamics and stock returns. We find that ex-post, the cost of creating OIVs is negligible and, to the contrary, often negative over our evaluation period: this means that OIVs that exploit and forecast bull and bear regimes end up producing realized performance that are better than those of strategies that do not. The origins of such gains lie in the fact that conditioning on sectorial dynamics, may lead to a more accurate identification and forecasting of regime shifts. Contrary to standard intuition, both ex-ante and ex-post, we find evidence that often an OIV ought to optimally invest in stocks issued either by firms that belong to the same sector that characterizes the OIV or at least from the same country as the OIV.

1. Introduction

To a dominant proportion of the active population, labor income implies an intrinsically large idiosyncratic component of risk caused by the existence of background risks. This is due to the fact that human capital tends to be inherently specialized and to lead individuals to pick stable occupations in specific sectors of the economy, which in turn are affected by business cycles as well as by sectorial/compositional shocks. Hence households and individuals look to capital markets as an important vehicle through which they may hedge their labor income risks.[1] Financial intermediaries have come to play a key

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[1] It is well known that human capital should affect optimal portfolio composition (see e.g., Merton, 1971; Mayers, 1972) to hedge labor income risk. Within labor income, industry risk plays a major statistical role, as implied by the magnitude and stability of inter-industry wage differentials in the US (see, e.g., Krueger and Summers, 1987; Weinberg, 2001), which points to the importance of the industry factor in the labor income process. International comparisons confirm this pattern in many OECD countries (see Kahn, 1998).

role in allowing households to hedge such risks and achieve rather complex diversification goals, not only in brokering a web of hedging and cash flow-recombining trades (e.g., by making a market in the required securities), but also by issuing financial products that may facilitate such operations, especially for relatively unsophisticated households; in this respect, financial intermediation arrangements such as mutual funds and pension funds naturally come to mind. In particular, pension funds would have the potential to help households to approach a tremendously difficult problem: how to maximize their (expected) welfare over a long investment horizon, when their background risks (e.g., wage risk) correlate in complicated and only partially predictable ways with the returns on the assets traded in the markets.

Building on a body of literature that has considered that risky labor income ought to affect investor portfolio decisions and hence have asset pricing implications (e.g., Bodie, Merton and Samuelson 1992; Danthine and Donaldson, 2002; Santos and Veronesi, 2006; and Kim, Kim and Min, 2011) and recent evidence demonstrating the consequences for portfolio choices (see e.g. Cocco, Gomes and Maenhout 2005; Benzoni, Collin-Dufresne and Goldstein, 2007; Angerer and Lam, 2009; Betermier, Jansson, Parlour and Walden, 2012) our paper examines how background risk affects optimal portfolio composition as households seek to hedge these risks. Specifically, our paper assesses the potential economic value that a particular class of investment vehicles—such as occupational pension funds—may generate through their ability to tailor on each group of households, as characterized by their occupation, appropriate investment strategies that take into account the existence of different degrees of symmetry and synchronicity of good and bad states across sectors and countries.[2] An occupational investment vehicle (henceforth, OIV) may be defined as an investment conduit that takes into account the age and occupation (hence, the properties of the wage/compensation process) of its stake-/share-holders when deciding on the optimal investment strategies to be applied to common asset menus, such as stocks, bonds, or a combination of both.

Importantly, our paper reports results for both the ex-ante and the ex-post economic value of OIVs. As it has been rather common in the literature (see e.g., Nicodano, Fugazza and Gioffré, 2011), ex-ante economic values are computed by examining the in-sample improvement in the achievable risk-return trade-off (sometimes captured by an expected utility value) when a fund strategy is explicitly conditioned on the dynamic properties of the wage/occupational cash flows of its shareholders. However, because these are in-sample evaluations, *ex-ante* economic values may fail to materialize in practice for a variety of reasons, such as bad luck over relatively short samples (i.e., an OIV that works over a typically long horizon may disappoint over much shorter horizons) and especially because the underlying asset allocation model is misspecified. Therefore, in our paper we systematically compute and report also *ex-post*, realized measures of economic value obtained through recursive, pseudo out-of-sample exercises that simulate the realized utility that an OIV would have produced for its shareholders in real time, assuming its optimizing strategies had been implemented over a given back-testing period. To our knowledge, this ex-post, realized real time assessment of the costs/benefits from OIVs has never been explored before. Both in the case of ex-ante and of ex-post economic value assessments, these are systematically

[2]Horneff, Maurer and Rogalla (2010) examine the portfolio choice problem where deferred annuities are part of the asset menu, documenting that such annuities should play an important role and form a significant part of a household's portfolio.

compared to the performance that would have been obtained instead by a generalist investment vehicle, that disregards the underlying background risk of its shareholders. We conjecture (see Sections 5 and 6) that OIVs have the potential to generate considerable economic value both in an ex-ante and—more importantly—in an ex-post perspective.

Nicodano et al. (2011) provide some preliminary evidence, quantifying differences in optimal equity portfolios across investors belonging to different industry-country pairs over the period 1998-2004. In particular, they compute the optimal international equity diversification decisions of US, Canadian and Italian investors working in seven different industries and compare these industry-based portfolios to the nationally-restricted portfolios, i.e., the set of weights that would be optimal for an investor endowed with the average home-country labor income. Overall, their analysis uncovers remarkable heterogeneity across industries in three countries pointing to a clear-cut role of occupational pension funds. However, their approach builds on Adler and Dumas's (1983) model where asset returns are simply IID, hence they are not predictable over time, and optimal portfolios only hedge deviations from the world inflation rate, implying that the market portfolio is not universally efficient as investors choose different risky portfolios according to their own country. Therefore no space is given to the effects of bear and bull regimes on the effectiveness of equity diversification strategies. On the contrary, our framework admits predictability, in the form of regime shifts jointly affecting both wages and asset returns.

The basic intuition of our normative approach is simple: most households (especially, highly specialized workers, with a strong chance of spending most of their careers in a limited number of related occupations and sectors) should find it optimal to channel their (pension) savings not in classical, general purpose, open-end funds, but instead in OIVs, e.g., pension funds with portfolio strategies that take into consideration the state and dynamics of the underlying sector. In particular, it has been suggested that OIVs should be designed to exploit the low (or negative) cross-sector stock return correlations to provide a hedge to their members' labor income shocks at the industry level.[3] However, such a view of the advantages of OIVs may be simplistic at best. First, because risk-averse investors attribute a higher marginal utility-weighted value to decreases in wealth than to increases in wealth, emphasis should be placed not on the average (unconditional) value of international cross-sector correlations, but especially on the values of such correlations during business cycle downturns and/or bear market states, when labor incomes may decline and stock returns are persistently negative. Second, we know from much recent empirical finance research that stock market bulls and bears may quickly move across borders (see e.g., Engle and Rangel, 2007; Guidolin and Timmermann, 2008). This means that when stock markets decline, they all do so together; when economies enter a recession, they often do so in synchronous ways. Therefore, the implication is that an OIV should try to deliver a high risk-adjusted performance taking these features into account. Indeed, Lynch and Tan (2011) demonstrate that predictability of labor income along with business-cycle dynamics play a key role in portfolio decisions. However their analysis

[3]Nicodano et al. (2011) make this argument with explicit reference to low international cross-sectoral correlations and derive implications for the home country bias in equity portfolios. We examine the potential benefits of both domestic and international equity diversification. In fact, it is the very evidence of a home bias that makes it crucial for us to examine the value of OIVs when these limit themselves to domestic equity investments.

is limited to linear predictability, while recent work on strategic asset allocation suggests that non-linear predictability deriving from regime switching models can produce both vastly different as well as superior portfolio outcomes than those using standard linear predictors both ex-ante (i.e., in sample) and ex-post, in realized recursive back-testing experiments (see e.g., Guidolin and Hyde, 2012). These are the reasons why we couch our out-of-sample experiment in a framework that systematically compares two types of asset allocation models: models that disregard predictability and therefore assume constant investment opportunities over time; bull and bear models of a Markov switching type in which persistent bull and bear market waves affect investment opportunities in ways that are easy to predict and therefore exploit.[4]

Using monthly data on sectorial and country stock returns and data on labor income compensations for the United States and the United Kingdom over a 1990-2010 sample period, we find three key results. First and foremost, with reference to two different countries, two asset menus each, and to a number of variations of the structure of the research design, we find that in realized, recursive out-of-sample terms, setting up OIVs to hedge labor income risks reflecting bull and bear dynamic patterns is essentially a *free lunch* for most (sometimes, all) potential OIVs under examination. The free lunch nature of the OIV structure derives from the fact that out-of-sample the realized performance measures that we compute indicate there is an effective *gain* in conditioning the OIV strategies to the dynamics of the labor income process that characterizes the sector to which the OIV refers to. This result is admittedly surprising and yet not impossible in out-of-sample tests, i.e., ex-post. It is surprising because ex-ante, we understand that constraining a portfolio choice program to also hedge labor income risks besides optimizing the risk-return trade-off typical of financial assets, ought to imply a non-negative expected utility costs. In fact, our paper had been originally geared towards the evaluation of the size of such costs. On the contrary, the finding of realized, negative performance costs (i.e., performance improvements) tends to dominate all of our experiments. Interestingly, estimates of simple two-state Markov switching models used to capture bull and bear states make it obvious where the origins of such improvements in realized performance lie: conditioning on sectorial, macroeconomic dynamics may lead to a better ability to identify and forecast regime shifts vs. the case in which only asset return data are employed. If such enhanced forecasting power delivers more accurate predictions over the back-testing sample, the net outcome may be that what ex-ante is just a potentially costly constraint, becomes ex-post a free lunch. In summary, resorting to OIVs as a matter of financial architecture may be less expensive than commonly thought.

A second and related point is that the realized performance of the OIVs we have simulated for the US and UK occupational sectors is considerably superior when OIV strategies are informed by a Markov switching model to capture non-linear predictability patterns in the data. The point here is not only or mostly that adopting regime switching models in asset allocation may improve realized out-of-sample performances compared to simpler, single-regime models (a point well-known since the analyses of Ang and Bekaert, 2004; Detemple, Garcia, and Rindisbacher, 2003; Guidolin and Hyde, 2012; Guidolin

[4]The effects of regime switching techniques on long-run pension/asset allocation problems has been already explored by Fraundorfer, Jachoby, and Schwendener (2007), who solve an asset and liability portfolio pension fund management problem under Markov switching involving the employment status of pension-seekers and asset returns. However, their paper does not make the case for OIVs or consider the realized, ex-post welfare gains of such a design.

and Timmermann, 2007), but instead that our assessment of the actual, realized performance cost of structuring OIVs to hedge labor income risks may be strongly affected by the statistical framework under which this assessment is performed.

A third and final result is that contrary to standard intuition, we have found evidence that—when optimal portfolio decisions are computed in a regime switching framework—often an OIV ought to optimally invest in stocks issued either by firms that belong to the same sector that characterizes the OIV or, more generally in international equity diversification problems, from the same country as the OIV under consideration. Importantly, such sector- or home-biased strategies seem to be optimal not only ex-ante but also ex-post because, as we have already mentioned, OIVs that exploit bull and bear dynamics regularly end up yield higher realized performances than strategies that do not. This happens because in a Markov switching framework it is possible for sectorial labor income payoffs to positively co-vary with sectorial stock returns, but also to negative co-vary with them in bear regimes, which is the state that tends to be over-weighted in optimal portfolio decisions by risk-averse investors.

The remainder of the paper is structured as follows. Section 2 describes the details of our research design. The data and preliminary empirical findings are discussed in section 3, while Section 4 presents the main findings of the paper in relation to recursive optimal portfolio weights and realized portfolio performance for domestic, purely sectorial allocations. Section 5 discusses the implications of background risk and predictability for international portfolio investments while section 6 performs robustness checks to identify whether the findings are sensitive to our specific design and data choice. Section 7 concludes.

2. Methodology

Consider a set up with M sectors within each country. Call $\mathbf{R}_t$ the $N \times 1$ vector that collects the net stock returns available in the asset menu, and $\mathbf{Y}_t$ the vector that collects the M labor income growth processes in each sector. Furthermore, call $\mathbf{Z}$ the $(N+M) \times 1$ vector that collects both the net stock returns and the labor income growth processes, $\mathbf{Z}_t \equiv [\mathbf{R}_t' \; \mathbf{Y}_t']'$. Clearly, when the asset menu is composed of equity portfolios that simply represent each of the sectors, then $N = M$. We assume that $\mathbf{Z}_t$ follows a two-state, pth order vector autoregressive regime switching model

$$\mathbf{Z}_t = \boldsymbol{\mu}_{S_t} + \mathbf{A}_{1,S_t}\mathbf{Z}_{t-1} + \mathbf{A}_{2,S_t}\mathbf{Z}_{t-2} + ... + \mathbf{A}_{p,S_t}\mathbf{Z}_{t-p} + \boldsymbol{\Sigma}_{S_t}\boldsymbol{\epsilon}_t \quad \boldsymbol{\epsilon}_t \sim IID\ N(\mathbf{0}, \mathbf{I}_{N+m}), \tag{1}$$

where the intercept vector, the VAR-type matrices of vector-autoregressive coefficients, and the Choleski factor of the covariance matrix of the shocks to the system ($\boldsymbol{\Omega}_{S_t} = \boldsymbol{\Sigma}_{S_t}\boldsymbol{\Sigma}_{S_t}'$) all depend on the current (but unobservable) state, $S_t = 1, 2$. We shall assume that the state variable S_t follows a simple ergodic and irreducible first-order two-state Markov chain (e.g., bad and good business cycle regimes), characterized by the (constant) probabilities, p_{11} and p_{22}, that the state may remain in state 1 and 2, respectively, between t and $t+1$, i.e., $p_{ij} = \Pr\{S_{t+1} = j|S_t = i\}$:

$$\mathbf{P} \equiv \begin{bmatrix} \Pr\{S_{t+1} = 1|S_t = 1\} & \Pr\{S_{t+1} = 2|S_t = 1\} \\ \Pr\{S_{t+1} = 1|S_t = 2\} & \Pr\{S_{t+1} = 2|S_t = 2\} \end{bmatrix} = \begin{bmatrix} p_{11} & 1 - p_{11} \\ 1 - p_{22} & p_{22} \end{bmatrix}. \tag{2}$$

The model in (1) captures the "association" (co-movement) between each sector-specific labor income process and asset-specific stock returns (i.e. $Y_{m,t}$ and $R_{n,t}$ respectively with $n = 1, ..., N$ and $m = 1, ..., M$), in three ways. First, through the potentially non-zero elements of the VAR(j) matrices $\mathbf{A}_{1,S_t}$, ..., $\mathbf{A}_{p,S_t}$ ($j = 1, 2, ..., p$) that create co-movements between persistent variables over time. For instance, labor income growth in sector m at time $t - j$ may predict stock returns on asset n at time t, for instance as a reflection of the dynamics of labor costs and profitability across sectors; in the same way, asset returns in sector m at time $t - j$ may predict labor income growth in sector n at time t, for instance as a result of a process of re-negotiation of labor contracts as a result of the specific sectorial conditions at time t (this is of course very likely when the asset menu consists of sectorial portfolios and $m = n$). Notice that this effect does not require the presence of regime switching. Second, the correlations between the shocks collected in $\boldsymbol{\epsilon}_t$ simultaneously affect the overall degree of association between sectorial labor income growth and stock returns. Also in this case, the effect does not require regime switching. Third, when across sector-specific labor incomes and stock returns the coefficient matrices ($\boldsymbol{\mu}_{S_t}$, $\mathbf{A}_{S_t}$, and $\boldsymbol{\Sigma}_{S_t}$) tend to move between regimes in similar/different ways, the result is to increase/decrease the association between income growth and stock return series (equivalently, the overall, unconditional correlation over/below the level simply measured by $\boldsymbol{\Omega}_{S_t}$).

Two restricted versions of (1) are also employed in this paper as natural benchmarks. When S_t can only take one value so that there are no regime shifts over time, then (1) simplifies to a standard VAR(p) framework,

$$\mathbf{Z}_t = \boldsymbol{\mu} + \mathbf{A}_1\mathbf{Z}_{t-1} + \mathbf{A}_2\mathbf{Z}_{t-2} + ... + \mathbf{A}_p\mathbf{Z}_{t-p} + \boldsymbol{\Sigma}\boldsymbol{\epsilon}_t \quad \boldsymbol{\epsilon}_t \sim IID\ N(\mathbf{0}, \mathbf{I}_{2N}), \tag{3}$$

which implies that both stock returns and labor income growth rates are predictable, but only in a linear fashion, either because the VAR matrices imply that past values of the variables in $\mathbf{Z}$ may predict future values, or because the shocks collected in $\boldsymbol{\Sigma}\boldsymbol{\epsilon}_t$ are simultaneously correlated. In this case stock returns and background risks co-move but not because they may simultaneously go through bull/expansionary and bear/contractionary, persistent regimes. When S_t can only take one value so that there are no regime shifts over time and $\mathbf{A}_1 = ...= \mathbf{A}_p = \mathbf{O}$, then the VAR($p$) simplifies to a standard Gaussian IID model, $\mathbf{Z}_t = \boldsymbol{\mu} + \boldsymbol{\Sigma}\boldsymbol{\epsilon}_t$ with $\boldsymbol{\epsilon}_t \sim IID\ N(\mathbf{0}, \mathbf{I}_{N+M})$, in which neither returns or labor income growth are predictable using past information and the only effect that the model may pick up is the simultaneous correlation of shocks through the off-diagonal elements of the Choleski covariance matrix factor $\boldsymbol{\Sigma}$.

Assuming that (1) is a realistic description of the joint, multivariate process followed by equity returns and labor incomes growth, consider an OIV's portfolio manager that aims at maximizing expected utility from terminal wealth for an agent/worker with horizon H occupied in sector $m = 1, ..., M$ by choosing the $N \times 1$ optimal portfolio weights ($\boldsymbol{\omega}_t^m(H) \equiv [\omega_{1,t}^m(H)\ \omega_{2,t}^m(H)\ ...\ \omega_{N,t}^m(H)]'$), when preferences are described by a simple mean variance objective,

$$\max_{\boldsymbol{\omega}_t^m} E_t\left[R_{P,H}^m\right] - \lambda_m Var_t\left[R_{P,H}^m\right], \tag{4}$$

where λ_m is the coefficient of (absolute) risk aversion of the worker from sector m, $R_{P,H}^m$ is the H-step cumulative return on the overall—i.e., including both her portfolio investments as well as her human capital—portfolio of the employee in sector m,

$$\begin{aligned} R^m_{P,H} &= (1-\eta)\left[\sum_{n=1}^N \omega^m_{n,t}(H)\prod_{\tau=1}^H(1+R_{n,t+\tau}) + \left(1-\sum_{n=1}^N \omega^m_{n,t}(H)\right)\prod_{\tau=1}^H(1+R^f_{t+\tau})\right] + \eta\prod_{\tau=1}^H(1+Y^m_{t+\tau}) - 1 \\ &= (1-\eta)\left[(\boldsymbol{\omega}^m_t(H))'\prod_{\tau=1}^H(\mathbf{1}+\mathbf{R}_{t+\tau}) + (1-(\boldsymbol{\omega}^m_t(H))'\mathbf{1})\prod_{\tau=1}^H(1+R^f_{t+\tau})\right] + \eta\prod_{\tau=1}^H(1+Y^m_{t+\tau}) - 1 \quad (5)\end{aligned}$$

where η denotes the labor-to-capital income share ratio and $R^f_{t+\tau}$ is the one-period short-term interest rate (riskless for investments between t and $t+1$). In what follows, for simplicity, these short-term rates are assumed to be known in advance. While wealth can be invested in each of the N different assets, by purchasing shares of stocks, as well as be left in cash earning the (riskless) short-term rate, the rate of return of overall wealth also depends on the rate of growth of labor income that is specific to sector m, $Y^m_{t+\tau}$ $\tau = 1,..., H$, because the agent is assumed to be employed by it. Notice that this definition of total wealth returns stresses that the properties of the stochastic process of $R^m_{P,H}$ will depend on the pair-wise correlations between the sector-specific labor income growth process $Y^m_{t+\tau}$ and each of the net, asset-specific stock returns $R_{n,t+\tau}$ for all $\tau = 1, 2, ..., H$. Interestingly, it is not only contemporaneous correlations that matter, but—at least for long-horizon investors with $H \geq 2$—also or even mostly the cross-serial correlations involving stock returns and labor income growth. Importantly, the conditional expectations and (co)variance operators in (4) simply condition on all the available information as of time t. When appropriate, this means that the objective in (4) may turn into

$$\max_{\boldsymbol{\omega}^m_t} E\left[R^m_{P,H}|S_t, \mathbf{Z}_t, \mathbf{Z}_{t-1}, ..., \mathbf{Z}_{t-p+1}\right] - \lambda_m Var\left[R^m_{P,H}|S_t, \mathbf{Z}_t, \mathbf{Z}_{t-1}, ..., \mathbf{Z}_{t-p+1}\right], \quad (6)$$

i.e., the moments may be computed conditioning on any information on the current regime (this is because we have assumed that the Markov chain is simply first-order), as well as on any relevant, lagged information to be used in (1).[5]

Solving the portfolio choice problem in (4)-(5) is a routine endeavor: the first-order conditions of the problem are

$$\begin{aligned}(1-\eta)\left[E_t\left(\prod_{\tau=1}^H(\mathbf{1}+\mathbf{R}_{t+\tau})\right) - \mathbf{1}\prod_{\tau=1}^H(1+R^f_{t+\tau})\right] - \lambda(1-\eta)^2\left\{Var_t\left[\prod_{\tau=1}^H(\mathbf{1}+\mathbf{R}_{t+\tau})\right]\boldsymbol{\omega}^m_t(H)\right\} + \\ - \lambda\eta(1-\eta)Cov_t\left[\prod_{\tau=1}^H(\mathbf{1}+\mathbf{R}_{t+\tau}), \prod_{\tau=1}^H(1+Y^m_{t+\tau})\right] = \mathbf{0},\end{aligned}$$

where $\mathbf{1}$ is a $N \times 1$ vector of ones, and $Cov_t\left[\prod_{\tau=1}^H(\mathbf{1}+\mathbf{R}_{t+\tau}), \prod_{\tau=1}^H(1+Y^m_{t+\tau})\right]$ is a $N \times 1$ vector of conditional covariances between the gross, H-period returns on each of the assets and the gross labor income growth rate of the mth sector, which is the one in which the portfolio optimizer is currently

[5] In the case of single-state VAR(p) models, this expression reduces to

$$\max_{\boldsymbol{\omega}^m_t} E\left[R^m_{P,H}|\mathbf{Z}_t, \mathbf{Z}_{t-1}, ..., \mathbf{Z}_{t-p+1}\right] - \lambda_m Var\left[R^m_{P,H}|\mathbf{Z}_t, \mathbf{Z}_{t-1}, ..., \mathbf{Z}_{t-p+1}\right].$$

In the Gaussian IID case, because of the absence of predictability, conditional and unconditional moments will be the same so that a worker/OIV will simply maximize $E\left[R^m_{P,H}\right] - \lambda_m Var\left[R^m_{P,H}\right]$.

employed. Solving the set of first-order conditions to find the optimal portfolio weights simply yields:

$$\hat{\boldsymbol{\omega}}_t^m(H) = \left\{Var_t\left[\prod_{\tau=1}^{H}(\mathbf{1}+\mathbf{R}_{t+\tau})\right]\right\}^{-1}\frac{E_t\left(\prod_{\tau=1}^{H}(\mathbf{1}+\mathbf{R}_{t+\tau})\right)-\mathbf{1}\prod_{\tau=1}^{H}(1+R^f_{t+\tau})}{\lambda(1-\eta)}+$$
$$-\frac{\eta}{1-\eta}\left\{Var_t\left[\prod_{\tau=1}^{H}(\mathbf{1}+\mathbf{R}_{t+\tau})\right]\right\}^{-1}Cov_t\left[\prod_{\tau=1}^{H}(\mathbf{1}+\mathbf{R}_{t+\tau}),\prod_{\tau=1}^{H}(1+Y^m_{t+\tau})\right]. \quad (7)$$

The formula in (7) reveals a rather standard finding: the classical, static mean-variance vector

$$\left\{Var_t\left[\prod_{\tau=1}^{H}(\mathbf{1}+\mathbf{R}_{t+\tau})\right]\right\}^{-1}\frac{E_t\left(\prod_{\tau=1}^{H}(\mathbf{1}+\mathbf{R}_{t+\tau})\right)-\mathbf{1}\prod_{\tau=1}^{H}(1+R^f_{t+\tau})}{\lambda(1-\eta)} \quad (8)$$

needs to be corrected in each of its N components by subtracting the vector

$$\frac{\eta}{1-\eta}\left\{Var_t\left[\prod_{\tau=1}^{H}(\mathbf{1}+\mathbf{R}_{t+\tau})\right]\right\}^{-1}Cov\left[\prod_{\tau=1}^{H}(\mathbf{1}+\mathbf{R}_{t+\tau}),\prod_{\tau=1}^{H}(1+Y^m_{t+\tau})\right]. \quad (9)$$

Since $\eta/(1-\eta)>0$, the elements of this vector are positive (negative)—hence, they increase the weight of stock/asset n vs. the classical static mean-variance demand for a stock—when $Cov[\prod_{\tau=1}^{H}(1+R_{n,t+\tau}),$ $\prod_{\tau=1}^{H}(1+Y^m_{t+\tau})]$ is negative (positive), i.e., for those assets that have stock returns that negatively (positively) co-vary with labor income in sector m and that therefore (fail to) help hedging background risks specific to a worker in sector m. Finally, as one would intuitively expect, the role of this background, sector-specific hedging demand is the largest the higher is the parameter η, here the labor-to-capital income share ratio.

The portfolio choice problem in (4)-(5) can also be solved imposing no short-sale constraints, i.e., $\omega^m_{n,t}(H)\in[0,1]$ for $n=1,2,...,N$. In this case, it is well-known that (4)-(5) must be solved with numerical methods. Given the relative simplicity of our portfolio program in this paper (e.g., the lack of a need to apply backward dynamic recursions), we resort to a simple grid search algorithm on a fine grid of points with a mesh of 0.2%, for a total number of points that is much lower than 51^N because of the unit summing up constraint that $(\boldsymbol{\omega}_t^m(H))'\mathbf{1}=1$.

2.1. *The Recursive Exercise and Performance Measurement*

We employ a (pseudo) out-of-sample (OOS) experiment with a recursive structure using an expanding window to examine the performance of the various models with respect to $M+2$ different scenarios regarding background risk:

- No background, labor income risk, when the recursive asset allocation problem corresponds to a classical mean-variance portfolio choice problem;
- Average background, labor income risk, when the recursive asset allocation problem is solved not for a worker with a specific, assigned sectorial allocation but instead for an (equally-weighted) average worker that is meant to be representative of the average worker of a given country;
- M sector-specific recursive asset allocation exercises, in which the optimally diversified portfolio is computed under M alternative sub-scenarios identified by the sector of employment to which the agent/worker belongs to.

The first scenario is an obvious benchmark in which, because background risk is absent, OIVs become irrelevant or, equivalently, each country ought to offer one aggregate OIV that ignores labor income. The second scenario also predicates the existence of a single, unique OIV but for a different reason: if workers from all sectors may find a way to share labor income risk in a uniform way by forming some form of (hard to envision) aggregate insurance scheme that smooths out labor income growth fluctuations, the resulting single OIV will conform to this second scenario. The third group of M are the focus of our research question and each may be considered as a stylized OIV.[6]

For each of the countries under examination, the exercise is performed recursively and conforms to standard back-testing requirement: at each point in time t, the OIV(s) under consideration are simply provided with the information in the data available up to time t, with any hindsight bias. For instance, in the case of the U.S. data set, we estimate all competing models using information for the period 1990:02-2001:12 and proceed to compute portfolio weights at horizons $H = 1, 12$ and 60 months. The estimation sample is then extended by one additional month, to the period 1999:02-2002:01, producing again portfolio weights at horizons of 1, 12 and 60 months. This process of recursive estimation, forecasting, and portfolio solution is repeated until reach the last possible sample, 1999:02-2009:12.[7]

To evaluate the out-of-sample portfolio performance of the OIVs, we compute the out-of-sample Sharpe Ratio for each portfolio strategy, defined as

$$SR_t^n(H) \equiv \frac{\prod_{h=1}^T (1 + r_{P,t+h}^{n,H}) - \prod_{h=1}^T (1 + R_{t+h}^f)}{\sqrt{\frac{1}{T-H} \sum_{t=1}^T (r_{P,t+h}^{n,H} - T^{-1} \sum_{t=1}^T r_{P,t+h}^{n,H})^2}} \tag{10}$$

$$r_{P,t+h}^{m,H} = \sum_{n=1}^N \omega_{n,t}^m(H)(1 + R_{n,t+\tau}) + \left(1 - \sum_{n=1}^N \omega_{n,t}^m(H)\right)(1 + R_{t+\tau}^f) - 1 \tag{11}$$

where R_t^f is the 1-month short-term rate, $r_{p,t+h}^{m,H}$ is the realized portfolio return on a H-horizon strategy implemented by a worker in sector $m = 1, ..., M$, and T is the total sample size in our data. On the one hand, the use of the Sharpe ratio to rank the realized performance of alternative OIVs is perfectly consistent with the mean-variance objective adopted in (4). On the other hand, notice that these recursive, realized out-of-sample Sharpe ratios are computed only with reference to realized financial returns. This is consistent with our goal of assessing how and whether OIVs may imply a net, realized welfare cost that is as high as sometimes claimed. As we shall see, the results are often contrary to this initially sensible conjecture, but that is only valid in-sample.

3. Data and Preliminary Evidence

We examine data on sectorial stock returns and labor income growth for two countries, the United States and the United Kingdom. Besides their relevance in terms of sheer size of their respective economies and importance of their capital markets, our choice is driven by the availability of good quality data on the

[6] We also entertain the case where an investor follows a 1/N portfolio strategy irrespective of labor income.

[7] Of course, the estimation process also implies that horizon $T \geq 2$ weights are computed for 2009:12. However, notice that given the structure of the data set, recursive out-of-sample performance evaluation will be feasible only for weights up to 2009:12$-T$ months.

rates of growth of sectorial labor income, over a sufficiently long period of time. However, for clarity, to save space and also because of the different length of the corresponding time series, we use the US as our baseline case, while calculations and evidence for UK data are used as a robustness check in Section 6, with detailed results available in an Appendix from the authors. In either case, we perform portfolio back-testing calculations with reference to two distinct, equally relevant asset menus: a domestic, recursive diversification exercise in which OIVs allocate wealth across alternative sectors (Section 4) and a second exercise (Section 5) based on an international asset menu, in which sectorial OIVs are called to diversify across macro equity portfolios as popularized by MSCI, similar to the exercise in Nicodano et al. (2011).

For both the US and the UK, we collect monthly series of growth rates for earnings (total compensations, including wages per hour) for a variety of sectors.[8] In the case of the US, the source is the Bureau of Labor Statistics (BLS) and the sample period is 1990:02-2009:12, for a total of 239 observations per series. We originally collect earnings growth series for 36 sectors and then aggregate the series into 11 sectors (these are: non durable goods, durables, manufacturing, energy, chemicals, business equipment, telecommunications, utilities, shops and retails, health care, and money/banking/finance) which corresponds to a typical sectorial disaggregation used in empirical finance studies, for instance as made available by Ken French in his data repository. The aggregation down from 36 to the 11 final sectors used in our study is based on the underlying SIC codes, and is performed by weighting each of the original series by aggregate hours worked, which gives a sense for the economic size of each of the sectors. For instance, BLS compensation dynamics for wood products, food, beverage & tobacco, textile products, apparel manufacturing, and leather products are all aggregated in the non-durables sector; the household and institutional furniture and appliance manufacturing, motor vehicles, motor vehicles bodies and trailers, and motor vehicle parts are all aggregated in the durables sector.

As for the UK, the source of the wage and compensation data is the Office of National Statistics (ONS) which compiles growth rate data for 15 different sectors of economic activity for the period January 2000 - December 2010, a total of 132 monthly observations. These data are aggregated into 7 macro sectors—these are industry (ONS codes DA, DG, DC, DJ, DK, DL, and DM), agriculture, forestry and fishing (codes A and B), mining, natural resources and quarrying (C), electricity, gas and water supply (E), construction (F), retail trade and repairs (G), and financial intermediation (J). The aggregation down from 15 to the 7 sectors used based on the underlying SIC codes is performed by weighting each of the original series by the total market capitalization (based on stock market indices) of the matching stock market indices (see below).

Data on sector equity returns are collected in the case of the US from Ken French's data repository and concern 11 sectors out of the typical 12-sector SIC-based classification; the twelfth, residual sector ("Others") is dropped since it is not meaningful for our study. The data are monthly, value-weighted,

[8]Although it would be certainly interesting to extend our analysis to a longer list of countries, data limitations—in the form of longer time series for sectoral wage growth rates—allow us to perform the analysis embracing the perspective of US and UK households only. Nicodano et al. (2011) have also investigated optimal weights for Canada and Italy (but not the UK), but their asset allocation model counterfactually assumes that stock returns and wage growth rates follows a Gaussian IID process, which limits their data and estimation requirements to simple, single-state regressions.

and their underlying sources are NYSE, NASDAQ, and AMEX price and dividends (distributions) data for the period 1990:02 - 2009:12. Data on sector equity returns in the case of the UK are from FTSE (available from Bloomberg), and the over 40 indices provided for the 2000-2010 sample period are aggregated (on market value-weighted terms) to match the 7 sectorial compensation growth series listed above. Sector total return equity indices for aeroplanes and defense supplies, automobiles, beverages, chemicals, electronic equipment, food and tobacco, pharmaceuticals and biotechnologies, industrial metallurgy, and industrial engineering are matched to "Industry"; the FTSE forestry and agriculture indices match the "Agriculture, Forestry and Fishing" ONS compensation index; the FTSE mining, oil, and gas indices match "Mining, Natural Resources, and Quarrying"; the equity indices for electricity matches "Electricity, Gas and Water Supply"; FTSE data on constructions and materials are matched with the ONS "Construction" wage series; FTSE data on food and drugs retailing, and general retailing with "Retail Trade and Repairs"; finally, stock return series on banks, life and non-life insurance companies, investment management, and financial services are matched to the "Financial Intermediation" series.

In addition to industry and sector equity data, we also collect aggregate MSCI international stock returns to examine the impact of background risk and the importance of bull and bear markets on international portfolio diversification, similarly to Nicodano et al. (2011). For the US investor, we collect returns on the US, Canada, UK, Japan, Europe excluding the UK and Asia excluding Japan. Similarly for a UK investor we examine UK returns plus returns on a North America portfolio, Japan, Europe excluding the UK and Asia excluding Japan. All returns are expressed in local currencies, which implies that we assume that our OIVs can completely hedge any exchange rate risk.

Table 1 reports means and standard deviations for monthly stock return and employee compensation growth data. Values are typical for the sample periods under investigation. Sectorial stock return data have means ranging from 0.31% per month (UK retail trade and repairs) to 1.18% (UK Industrials) and standard deviations ranging from 3.97% per month (US non durables) to 7.70% per month (US business equipment). Also all the data on compensation growth rates in Table 1 conform to prior expectations, sample means are positive and exceed the rate of inflation for the period (which is to be expected, when productivity increases, as it has over our sample), with lows of 0.37% (UK financial intermediation, a likely outcome of the 2000-2010 sample being dominated by the 2008-2009 financial crisis) and a stunning high of 1.27% (UK mining and quarrying). Standard deviations are of the same order of magnitude as returns—due to the fact that we consider total compensation packages and not only nominal salaries and wages, which are notorious for being rather sticky—ranging from 1.03% (UK financial intermediation) to 9.17% (UK mining and quarrying).

3.1. *Regimes in US Sector Stock Returns*

We start by considering the case in which $N = M$ because the asset menu is composed by the same sectorial portfolios that characterize background, labor income risk. Our baseline Markov switching model is a restricted version of (1) in which $p = 0$ so that $\mathbf{A}_{1,S} = \mathbf{O}$ in both regimes and in which the elements of $\mathbf{\Sigma}_S$ $(S = 1, 2)$ which collect covariances between the compensation growth process of any possible pair of employment sectors (say, manufacturing and utilities) are set to zero. The reason for these restrictions are different. The zero covariance restrictions on $\mathbf{\Sigma}_S$ simply derive from the fact that such covariances are irrelevant to portfolio choice and therefore to our problem under the simplifying (but rather realistic) assumption that each individual (or head-of-household) holds a job in one and only one of the sectors we have data for. Obviously, such a restriction also implies the possibility of greatly reducing the number of parameters to be estimated by as many as $N(N-1)/2$. For instance, with 11 sectors this is a hefty 55 parameters per regime. The VAR(0)-type restriction by which $\mathbf{A}_S = \mathbf{O}$ in both regimes, has two different motivations. First, in general, both likelihood ratio tests and information criteria allow us (although only marginally in the latter case) to "not reject" the null hypothesis that a VAR(0) is appropriate to describe the data at hand. Second, setting $\mathbf{A}_S = \mathbf{O}$ implies an enormous contraction in the number of parameters to be estimated, as their total number shrinks by as many as 484 parameters per regime! All in all, this pair of restrictions implies that while—with $N = 11$ sectors—in principle, (1) would require the need to estimate 1518 parameters, the restricted model[9]

$$\mathbf{Z}_t = \boldsymbol{\mu}_{S_t} + \mathbf{\Sigma}^*_{S_t}\boldsymbol{\epsilon}_t \quad \boldsymbol{\epsilon}_t \sim IID\ N(\mathbf{0}, \mathbf{I}_{22}), \tag{12}$$

where $\mathbf{\Sigma}^*_{S_t}$ incorporates the zero restrictions mentioned above, implies the estimation of only 442 parameters; with a total of 5,258 observations, this means that 11.9 observations per parameter are available on average, which is normally considered a low but acceptable (saturation) ratio in non-linear estimation.

We have also compared—using both likelihood ratio tests that adjust for nuisance parameter problems under the null of a single regime and information criteria suitable to compare the non-linear econometric frameworks—the fit of the restricted Markov switching model in (12) with the fit provided by both Gaussian IID models and VAR(p) models with only one regime and always "rejected" the null of a single regime with very high confidence.[10]

For clarity, even though only one large, multivariate regime switching model has been estimated, Tables 2, 3, and 4 report parameter estimates concerning stock returns, labor income growth, and covariances separately. Table 2 reports the full sample ML/EM parameter estimates for this model for the sector stock return series, the $N \times 1$ vector $\mathbf{R}$. The typical characteristics of the bull and bear states can be observed, with the bear state yielding negative mean returns in 10 sectors out of 11; in 8 of these cases, the estimated means are statistically significant with p-values of 0.05 or lower;[11] in the bear state standard deviations (volatility) are higher compared to the bull state as well as higher than the average, unconditional volatilities over the full-sample. In fact, the bear state average (across the 11 sectors)

[9] Apart from issues of whether such an estimation exercise may be sensible, because with a total of 5,258 observations (22×239 observations) it appears not prudent to try and estimate more than 1,000 parameters, we have not been able to obtain numerical convergence for this problem.

[10] For instance, we have performed an adjusted likelihood ratio test with nuisance parameter adjustment à la Turner, Startz and Nelson (1989) (by which the test statistic $-2(T-3)[\ln L(\tilde{\boldsymbol{\theta}}) - \ln L(\tilde{\boldsymbol{\theta}}_r)]/T \xrightarrow{D} \chi^2_r$, where $\tilde{\boldsymbol{\theta}}_r$ is obtained under the null of single-state IID normality and $r = K(K-1)$) obtaining a p-value of 0.001. The Hannan-Quinn informationn criterion for the two-state model is 61.09, considerably lower than the 61.71 implied by a single-state Gaussian IID model.

[11] The only positive mean coefficient in the bear state concerns the health sector, with an small average monthly return of 0.10% which is however not statistically significant (the corresponding p-value is 0.485). In the case of two other sectors, non-durables and shops & retail, the estimated bear state mean returns are negative but not statistically significant.

volatility is a 7.4 percent per month, which translates into a rather high annualized volatility of 25.8 percent. Some sectors are in fact highly volatile, with peaks in excess of 8-10% per month (i.e., around 30% in annualized terms) for durables, business equipment, and money and finance. Averaging across sectors in the bear regime, the expected stock return is -0.56 percent per month. Correspondingly, the associated Sharpe ratios are negative across all the 11 sectors (-0.11 on average across sectors). The second state is instead characterized by relatively high, statistically significant and positive mean returns (1.41% on average across all sectors) which are typical of bull states. In this state, volatility is also relatively low and always below the full-sample statistics for volatilities, on average across sectors a 4.2 percent per month (this is a 14.4% in annualized terms), that is, 44% lower than the average bear state volatility. The corresponding bull state Sharpe ratios are all high and closely clustered between 0.17 (for durables) and 0.34 (manufacturing), with a cross-sectorial average of 0.27.

Figure 1 reports the smoothed state probabilities implied by the full-sample ML/EM estimates of (12). The plots fully support our interpretation of the first state as a bear regime and of the second as a bull regime. In fact, there are three distinct episodes of the bear state which are easily recognizable: the Spring-Summer 1998 in correspondence to the Asian/Russian debt crises, the market downturn and official recession over 2000-2002, and the recent financial crisis in 2008-2009. The rest of the time the US stock markets were in a bull regime of high and positive mean returns and moderate volatilities. Interestingly, the periods of bear markets listed above correspond to an overall span of 62 months out of a total of 239, which is a 25.9% of our complete sample which nicely matches the long-run, ergodic probability of a bear regime implied by the estimated MS model, 25.7%. Figure 1 also shows that both states are clearly very persistent and have a rather high expected duration: more than 18 months in the case of the bear state and almost 53 months in the case of the bull regime. Such considerable persistence and extended expected durations are clearly relevant for portfolio choice purposes, even for investors with long horizons (e.g., the 53 month duration exceeds an already rather long 4-year horizon).

Table 3 presents estimates concerning stock returns and the regime-specific correlation matrices across returns, confirming a well-known fact: equity correlations are higher during bear states (the coefficients below the main diagonal), when prices are falling, than during bull states (the coefficients above the main diagonal). In fact, out of 55 possible pairs of correlations, in 31 cases the bear state correlation exceeds the bull state one. This is also highly relevant from an asset allocation perspective, since high correlations substantially reduce the benefits from diversification. Though there is evidence that sectors such as business equipment may act as a hedge of bear regimes, as their correlations with other sectors decline. However, it is also fair to observe that—with very few exceptions—most correlations are positive and statistically significant in both regimes, with the average correlations between 0.5 and 0.55 depending on the state assumed.

Table 4 reports the Markov switching estimates for the 11 series of sectorial compensation growth rates as well as their regime-dependent correlations with stock returns. Two points are of interest for our purposes. First, 8 sectors out of 11— the exceptions being manufacturing, telecommunications, and shops & retail—have either mean compensation growth rates or the standard deviation of compensation growth rates that are statistically different across bull and bear regimes. We formally test these differences performing likelihood ratio tests of equality restrictions (both separately and jointly for means and variances) and boldface the coefficients when any of the tests reject with p-values of 5% or lower. This is a key finding because in all these 8 cases, the patterns of estimated means and volatilities across regimes are *not* the same as the ones found for stock returns. Estimated mean growth rates appear to be often higher in the bear regime than they are in the bull regime, while it remains that estimated variances tend to be higher in the bear vs. the bull state. In fact, the estimated mean growth rate of labor income is 0.27% in the bear state vs. 0.26% across sectors, while the standard deviations are 0.73% vs. 0.68% across sectors. This implies that individuals occupied in these 8 sectors will face different diversification opportunities than standard correlation matrices may lead us to think. A worker would like to use financial markets to diversify away adverse labor income shocks and—to some extent, within any given state—Table 4 points to the fact that she may be able to do that. Moreover, across regimes, individuals in some sectors (4 out of 11, non-durables, chemicals, business equipment, and health care) may reap the additional benefit that their own labor income will be growing when stocks (generally speaking, in all the available investment sectors) are yielding zero or negative mean returns and appear to be substantially more volatile than they are on average. However, in 3 sectors (durable and utilities, plus one of the 4 sectors above, chemicals) the worker will also perceive the problem that her own labor income will be excessively volatile exactly at this point. Finally, in two sectors there is evidence that bull and bear dynamics may actually damage the diversification opportunities individuals face: in the energy and money & finance sectors, the mean (variance) of the compensation growth rate is lower (higher) in bear markets than they are in bull markets. These are sectors for which the demand of own-sector stocks by OIVs should be depressed relative to the case in which bull and bear dynamics are ignored. For the remaining 6 sectors, it is impossible to detect ex-ante how and whether the properties of labor incomes across bull and bear states will affect optimal portfolio choices by the corresponding OIVs.

There is a second, remarkable effect shown in Table 4. Regime-specific correlations of each sector compensation growth series with sectorial stock returns show, in general, correlations are smaller (more negative) in bear regimes than they are in bull states, and this represents a bonus that makes available stronger diversification opportunities exactly when a worker needs them, i.e., in bad financial states. In general, a high fraction of the correlation coefficients found from our MS estimates—more importantly, almost all the correlation coefficients that are statistically significant—are negative, indicating that negative (positive) shocks to labor income tend to come contemporaneously with positive (shocks) to stock returns.[12] Table 4 makes it obvious that in fact, while the bear regime generates almost all of the negative and statistically significant correlations, the bull state generally indicates that there is barely any correlations between the dynamics of labor incomes and of stock returns.

[12]Here we should be careful that a shock is defined as a deviation from the (possibly, regime-specific) mean: in a bad financial state, it is possible for labor income to increase slowly or fail to increase and yet it may be the result of a positive shock that raises it above its (low) conditional mean.

4. **Domestic Asset Allocation and Realized Recursive Portfolio Performance**

4.1. *Recursive Portfolio Weights*

Figure 2 presents the average (over the pseudo OOS period 2002:01 - 2009:12) equity sectorial portfolio composition assuming mild risk aversion preferences ($\lambda = 1$), a 1-month horizon under different assumptions regarding background risk in the form of sets of pie charts, and imposing no short-sale constraints.[13] The weights represented in the Figure correspond to the pure equity portfolio component, i.e., for clarity and comparability across different OIVs, we simply represent the equity portfolio shares. The figure has 13 different rows of 3 plots each. Each row corresponds to one of the $N + 2$ background risk scenarios discussed above. For each of the scenarios the figure plots the average portfolio composition for three alternative econometric models: the Gaussian IID model (no predictability, VAR(0), no Markov switching) benchmark on the left hand side, the VAR(1) (linear predictability) model in (3) in the middle, and the optimal sectorial diversification implied by the restricted Markov Switching (non-linear predictability) model in (12) on the right.[14] In the case of the 11 sectorial OIVs, the slice corresponding to the OIV's sector is the lightest colored slice (in gold when the paper is printed in color).[15] The first row of pie charts clearly shows that—even with no labor income risk—the Markov switching model produces portfolio weights which appear to be markedly different from those implied by either the Gaussian IID or VAR(1) models. Interestingly, in the first two rows of the figure the Gaussian IID and VAR(1) pie charts reveal a striking similarity, which shows that linear predictability patterns are insufficient to produce major effects on optimal weights. Yet, when these weights are computed under (12) the resulting portfolio shares imply that a much greater weight should placed into manufacturing, chemicals and telecoms while non-linear predictability implies no investment in non-durables, energy or business equipment.

The other visible implication of Markov switching is that it often *decreases* the share that should be invested by an OIV into the stocks issued by firms that belong to the reference sector of the OIV. This very evident in the case of the energy (where the share under MS is on average 17% vs. 24% when all forms of predictability are ignored), chemicals (1% under MS vs. 2% in the Gaussian IID case), business equipment (11% under MS vs. 18% in the Gaussian IID case), and money and finance (17% under MS vs. 29% in the Gaussian IID case) sectors. On the one hand, this corresponds to standard advise: a worker who wishes to avoid putting all of "her eggs" in the same basket ought to reduce as much as possible how much she invests in stocks issued by companies belonging to the same sector and therefore likely to share a similar macro-economic dynamics (not to mention stocks issued by the companies she is employed with). On the other hand, other sectors—significantly utilities, retail and shops, and health—are marked by an

[13] Even though Section 2 has entertained the general case in which λ_n may depend on the OIV under examination, in the rest of the paper we will simply assume that λ is common across sectors. However, to allow a Reader to form different, independent opinions 3 alternative values of λ are considered: $\lambda = 0.5$ (low risk aversion), $\lambda = 1$ (mild risk aversion), and $\lambda = 2$ (high risk aversion). Here one needs to recall that λ can be interpreted as an *absolute* risk aversion coefficient, for which values ranging between 0.2 and 2 are in fact typical of the finance literature.

[14] A single-state VAR(1) model is largely preferred to any other single-state model using information criteria when all sectors returns and labor income growth rates are jointly modeled, as described in Section 3.

[15] When the slice corresponds to a zero percentage weight, this emphasized by coloring the label of the OIV sector in gold (shading), like in the case of the investment of the chemical's OIV in chemical sector stocks.

increase in the share that should be invested by an OIV into the stocks issued by firms that belonging to the reference sector of the OIV. Interestingly, some of these effects also occur when we compare the OIV diversification choices from the linear predictability and the no predictability models, although the differences are often less important than the ones found above.[16]

We have also examined the exercise when no short sale constraints are imposed and the findings are similar to the ones reported above, of course only more extreme given the different nature of the portfolio problem. For instance, focussing again on the case of $\lambda = 1$ and of a 1-year horizon, it remains true that a Markov switching framework tends to imply that the OIV from a sector n ought to invest in stocks of firms belonging to sector n much more than advised by simpler linear or no predictability models: for the non-durables sector the weight increases from 46 to 81 percent, for the energy sector the weight increases from 54 to 120 percent, for the business equipment sector the increase is from 24 to 52 percent, and for the money and finance sector from 61 to 80 percent.[17] This result is due to the fact that while in the short-term, especially when predictability is ignored, it is indeed the case that most sectorial stocks tend to be positively correlated, with labor income growth this is generally not the case in the long term, especially when bull and bear states are ignored. This means that same-sector hedging demands that are negative in a classical mean-variance framework turn positive (or are less negative) for longer horizons and when the correlation induced by synchronous regimes are taken into account.

4.2. *Realized Recursive Portfolio Performance*

Our finding that predictability assumptions yield vastly different asset allocation weights for investors may have important implications for actual realized out-of-sample performance. Yet it is far from clear whether these different holdings give rise to significantly different performance. In particular, as discussed in the Introduction, whether an OIV ought to leave on the table a large portion of the realized Sharpe ratio potentially available because the workers investing through the OIV perceive hedging needs that may cause a structural deviation of their portfolio weights from the case of no background risk, remains an empirical issue.

Table 5 reports the realized recursive OOS Sharpe ratios for mean-variance optimizing portfolios under the various assumptions regarding background risk and predictability. The table reports (annualized), realized Sharpe ratios over the OOS period 2002:01-2009:12 for the 3 risk aversion coefficients (λ) and the 3 alternative horizons (H) analyzed in this paper for the case in which short-sale constraints are

[16] Summary statistics for 1-month, 1- and 5-year horizons show that the optimal portfolio shares remain qualitatively similar. Under the Gaussian IID model the weights hardly depend on the investment horizon because, at least as a first approximation, we know that under locally mean-variance preferences, in the absence of predictability optimal portfolio decisions ought to become independent of the horizon (see e.g., Merton, 1971). At a 1-year horizon we notice that in only one sector OIV (money and finance) there is a strong reduction in the portfolio weight invested by the OIV in the same sector when we go from a non-predictability benchmark (mean 29%; median 33%) to the MS model (mean 27%, median 30%). In three sectors (non-durables, durables, and business equipment) the share invested in the same sector is instead increasing as one takes bull and bear dynamics into account.

[17] The only example of an OIV that should invest less in stocks from firms of the sector than what the Gaussian IID model implies is the manufacturing sector, where the weight declines from 2 to -20 percent.

imposed. For ease of consultation, we have boldfaced—for each combination of λ and H—the highest realized Sharpe ratio across the three econometric models. In particular, we care about two questions. First, whether there are benefits from managing OIVs taking regimes into account. Second, whether the Sharpe ratios, even the best ones are inferior or superior to those investors may achieve in the absence of background risks. Table 6 shows that in the absence of labor income risks (the column "No") the highest realized recursive Sharpe ratios are obtained when regimes are ignored: from a simpler VAR(1) model for short and medium investment horizons (e.g., with a realized ratio of 0.47 for $H = 1$ month and 0.40 for $H = 12$ months when $\lambda = 1$), from a Gaussian IID model in the case of long horizons (0.12, again in the case $\lambda = 1$).[18] When the exercise is performed for some average worker whose labor income is the equally weighted average of all labor income growth processes under examination (the column "Avg."), one obtains realized Sharpe ratios that are generally close although mostly inferior (as one would expect, as hedging average labor income risks must come at a cost in terms of performance) to the ones found in the absence of labor income risks.

As for the first question, Table 5 shows that the highest Sharpe ratios are obtained when using the MS model and accounting for non-linear predictability irrespective of assumptions about risk aversion or the sector of employment. At the one month horizon the MS model is outperformed in only 5 cases (out of 39 cases) with the VAR model yielding better performance under no background risk at each level of risk aversion and for the average employee with high risk aversion, while the no predictability benchmark only performs best for employees in the durables sector with low risk aversion. Similarly, at the intermediate horizon, the MS model produces better OOS performance in 28 cases and in 26 cases at the long horizon. In fact, Table 6 reports the gain in realized Sharpe Ratio delivered to an OIV that chooses to replace a Gaussian IID benchmark with either a VAR model or a MS model that exploit predictability. From the table it is evident that accounting for predictability improves OOS performance in the majority of cases. In practice, such an improvement in performance turns uniformly positive and it is often large in the case of MS. For instance, for $\lambda = 1$ such a gain is on average (i.e., across the 11 OIVs under examination) a stunning 0.36 in the case of $H = 1$ month, 0.23 in the case of $H = 12$ months, and 0.08 for 5-year horizon OIVs. On average these improvements in Sharpe ratios are negative (e.g., -0.02 for $H = 1$ month) or rather small (0.02 at the long horizon and 0.12 at the intermediate horizon) in the case of a simpler VAR(1) model that ignores bull and bear dynamics in returns and labor income.

As for the second question, Table 7 shows surprising empirical findings. In the table we have computed the difference between the realized OOS Sharpe ratio in the absence of background risks (the column "No") and the realized OOS Sharpe ratio for each possible OIV, under both the linear and the non-linear predictability models. Positive values imply that investors suffer performance losses caused by their need to hedge labor income risk. While in-sample (ex-ante) we understand that these measures all have to be positive, in OOS (ex-post) back-testing exercises, this is not always the case. When predictability is ignored, this expectation is confirmed for all OIVs except one. In general, the same is true of the linear predictability model. However, for the MS model, in 66 cases (OIVs) out of a total of 99 (11 OIVs $\times$ 3

[18]Similarly following a 1/N strategy yields Sharpe Ratios of 0.49 ($H = 1$), 0.38 ($H = 12$) and 0.13 ($H = 60$).

risk aversion coefficients $\times$ 3 horizons), the striking result is that OIVs out-perform the case in which no hedging of labor income risk is presented. For instance, the average realized Sharpe ratio performance improvement is 0.13 for short-term OIVs, 0.09 for intermediate ones while there is only a small loss of 0.02 at the long horizon, even though almost half of the OIV do improve their performance when labor income risks are taken into account. This exceptional OOS performance for the combination between OIVs and Markov switching is due to the fact that a large number of estimated simultaneous correlation coefficients between labor income growth and own-stock returns are in fact negative in the regime in which an OIV has the highest pressure to provide diversification benefits for the poor performance of equity investments. For instance, in Table 4 it is easy to verify that such own correlation coefficients are significantly negative in 6 cases out of a possible 11; even when the coefficients are not statistically significant, their sign tends to be negative. The OIV that may benefit the most from a bear regime-driven diversification effect are non-durables, manufacturing, energy, business equipment, retail and shops, and money & finance, which are also approximately the same OIVs for which the negative bear state correlation of simultaneous shocks is stronger.[19] Of course, Table 4 also shows that such an effect disappears or fails to be statistically significant in the bull state. However, it is well known that a risk-averse investor will be more sensitive to avoid large losses in bad states than in good ones, and this different weighting of the own-risk hedging properties of labor income turn out to be strong enough to drive our OOS realized Sharpe ratio results. Finally, it rational to expect that this own-risk diversification effect may be stronger for more risk-averse investors, for short-term planning horizons, and for OIVs using econometric models that explicitly separate between bull and bear regimes. This is indeed what Tables 6 and 7 show: the performance loss of OIVs tend to be smaller or even negative (i.e., these turn into gains) exactly in the right-most upper panels—under Markov switching and short-term horizons of 1 month—and assuming high risk aversion coefficients of $\lambda = 2$.[20]

5. **International Portfolio Diversification**

To this juncture, we have solely examined whether an investor's employment status impacts their domestic portfolio holdings. We now consider whether the background risk faced by an investor has an impact on their international holdings. In this case, as already described in Section 3, we shall have $M = 11$ sectors as in Section 4, but $N = 6$, as represented by 6 typical MSCI aggregate/international portfolios with returns expressed in local currencies (i.e., under complete hedging). Not only is this a logically sensible exercise to perform since it is possible that the best way for an OIV to escape the local, sector-specific as well as the domestic business cycle influences may be to consider foreign equity diversification but also it acts to extend the in-sample results reported by Nicodano et al. (2011) to an out-of-sample recursive

[19] In a few cases, as already noticed, it also occurs that two-state MS parameter estimates for mean labor income growth rates do reveal that such a mean is significantly higher in bear the regime than in the bull regime, which provides a further channel of diversification of own-equity return risk for the corresponding OIV.

[20] In unreported results (available from the Authors upon request) we have performed the recursive OOS calculations afresh with short-sales admitted so that the formulas in (7) are directly used. Removing the constraints yields qualitatively consistent results though, as one would expect, performances are generally weaker once predictability is taken into account.

back-testing evaluation that spans both models with no predictability of returns as well as models with bull and bear dynamics à la Guidolin and Timmermann (2007).

5.1. *Bull and Bear Regimes in International Equity Returns*

Given the results from Section 4 concerning the relative performances of VAR(1) vs. MS models, in this Section we have entertained only two alternative econometric frameworks, the Gaussian IID and (12). As a matter of fact, the same type of covariance matrix restrictions employed in the case of the sectorial data set were not rejected in this case. In this case, with 11 sectors and 6 portfolios in which it is possible to invest, there are still 55 restrictions per regime coming from the simplified structure of the covariance matrix. The VAR(0)-type restriction by which $\mathbf{A}_S = \mathbf{O}$ in both regimes yields another 578 total restrictions. All in all, we need to estimate 232 parameters; with a total of 4,063 observations, this means that 17.5 observations per parameter are available on average, which is a rather typical saturation ratio in non-linear estimation. Also in this case, several criteria—such as likelihood ratio tests that adjust for nuisance parameters under the null of a single regime and information criteria—indicate that even after penalizing for the different size (an unrestricted Gaussian IID model implies 170 parameters to be estimated), the fit of the restricted Markov model in (12) is vastly superior to the fit provided by a simple Gaussian IID model and that the null of a single regime was always "rejected" with very high confidence.

Tables 8, 9, and 10 report parameter estimates concerning international stock portfolio returns, labor income growth, and covariances separately. Table 8 reports the full sample ML/EM parameter estimates and the typical characteristics of the bull and bear states can be observed, with the bear state yielding low (not statistically different from zero) or even negative mean returns for all portfolios. In the bear state, for 4 indices out of 6, standard deviations (volatility) are higher compared to the bull state as well as higher than the average, unconditional volatilities over the full-sample; in the remaining two cases, standard deviation does not seem to change across regimes. In fact, the bear state average (across the 6 portfolios) volatility is a 5.3 percent per month, which translates into a high annualized volatility of 18.4 percent. Averaging across sectors in the bear regime, the expected stock return is a puny 0.24 percent per month. Correspondingly, the associated Sharpe ratios are all small or even negative across all the 6 portfolios (essentially zero on average). The second state is instead characterized by relatively high, always statistically significant, and positive mean returns (0.74 percent on average across all sectors) which are typical of bull states. Volatility is also often lower than in the bear regime, on average across sectors a 4.7 percent per month (16.3% in annualized terms). The corresponding bull state Sharpe ratios are generally high (Japan is the only exception because of its protracted bear market) and close to a rather typical monthly 0.10. An unreported plot of the smoothed state probabilities implied by the full-sample ML/EM estimates of (12) supports our interpretation of the first state as a bear regime which picks up the brief recession and Kuwait invasion of 1992-1993, the recession and stock market bust of 2001-2004, and of course the recent 2008-2009 financial crisis and of the second as a bull regime.

Table 9 shows the regime-specific correlation matrices across stock return series only. The table confirms another widely acknowledge stylized fact (see e.g., Ang and Bekaert, 2002): international equity correlations are higher during bear states (the coefficients below the main diagonal), when prices are falling, than during bull states (the coefficients above the main diagonal). Surprisingly, in all cases/pairs of bull vs. bear correlations, the bear state correlation exceeds the bull state one; all estimated stock portfolio correlations are positive and statistically significant in both regimes, with the average correlations of 0.76 in the bear state and of 0.57 in the bull state. Finally, Table 10 reports the Markov switching estimates for the 11 series of sectorial compensation growth rates as well as their regime-dependent correlations with international equity returns. In 9 sectors, estimated mean growth rates appear to be higher in the bear than they are in the bull state; as a result, the estimated mean growth rate of labor income is 0.28% in the bear state vs. 0.23% in the bull state across sectors.[21] Individuals employed in these 9 sectors will face different diversification opportunities than what standard correlation matrices lead us to think and will to use international stock markets to diversify away adverse labor income shocks. Finally, out of a possible total of 66 estimated coefficients (11×6), in 40 cases we find that the estimated bear correlation between sectorial labor income growth and international stock returns are significantly negative. Such negative bear correlations are particularly large and imply p-values that are close to zero in the case of the business equipment, utilities, and shops & retail labor income sectors. On the contrary, this occurs only 23 times with reference to the bull state, and in 12 cases the estimate correlation coefficient is significantly positive. These estimates indicate that stronger diversification opportunities in international equity markets are available exactly when a worker needs them, i.e., in bad financial states.

5.2. *Recursive Portfolio Weights*

Similarly to Figure 2, Figure 3 presents the average (over the pseudo OOS period 2002:01 - 2009:12) international pure equity portfolio composition assuming mild risk aversion preferences ($\lambda = 1$), a 1-month horizon under different assumptions regarding background risk in the form of sets of pie charts, and imposing no short-sale constraints. The figure has 13 different rows of 2 plots each in correspondence to either a single-state Gaussian IID model (no predictability) benchmark on the left hand side or to the restricted Markov Switching model in (12), on the right. In all rows, because this recursive simulation exercise concerns US data, we highlight as a light-colored (gold) slice the percentage to be invested in U.S. stocks. Also, it is immediately clear that MS strongly affects optimal diversification, with or without any labor background risks taken into account. When background risks are ignored or these are averaged out and therefore largely diversified (second row of the figure), taking bull and bear dynamics into account tends to reduce the optimal share to be invested in domestic, US stocks.[22] For instance, in the first row of pie-charts, Figure 3 shows that on average, over our OOS period, while under a Gaussian IID

[21] However, we note that, taking averages is only indicative and not economically meaningful because in practice it is impossible to form cross-sectoral portfolios of labor income proceeds.

[22] This implies that MS-driven choices ought to be less optimally home-biased than simpler, single-state weights. This is consistent with Guidolin and Timmermann (2008), who report that in a simple mean-variance asset allocation framework, MS actually makes the optimal degree of home bias even lower than what one should expect under the equilibrium CAPM. However, when higher-order moments of future wealth are taken into account, this conclusion is over-turned and MS ends up explaining most of the home bias in equity portfolio decisions observed in the data.

model a ($\eta = 0$) investor ought to invest 68% in the US, 24% in the UK, and 6% in Canada, which represents a heavily Anglo-Saxon centered allocation, under MS almost all weight should be shifted towards UK stocks (80%), followed by 8% in Asian stocks (excluding Japan), with the US only absorbing 4% of invested wealth. Results are qualitatively similar when the averages refer to a composite, equally weighted US labor income earner. On the contrary, when background risks are taken into account into solving the portfolio choice problem, the general finding in Figure 3 is that the weight to be attributed to US stocks (hence, at least in some naive sense, the degree of average home bias in optimal allocations) tends to *increase* for most of the OIVs, when going from ignoring bull and bear regimes to taking them into account. Such a growing optimal home biased portfolio stance is particularly visible in the case of the non durables (from 54 to 60 percent), durables (from 36 to 52 percent), energy (from 40 to 53 percent), utilities (from 38 to 59 percent), and shops & retail (from 45 to 55 percent) sectorial OIVs. That background risks tilt the international diversification of OIVs towards domestically issued stocks is perfectly intuitive given the findings in Table 12 that most sectorial labor income growth processes tend to display higher means when the international stock markets—and leading among them the US markets—are in bear state, and that at least 6 sectors imply that their labor income process shocks negatively correlate with US stock returns in the bear state, exactly when risk-averse investor will be seeking for protection against adverse financial performance.

An unreported table (available upon request from the Authors) highlights that MS tends to deeply affect the optimal OIV portfolio shares with an interesting pattern emerging: as the horizon H grows, the weight optimally assigned by most OIVs to U.S. stocks declines, even rapidly in some cases. Typically as the U.S. weight declines, it is replaced either by European (ex-UK) stocks, or by Canadian stocks. The exact replacement patterns that dominate depend on the specific OIV under consideration, and therefore on the dynamic, bull and bear features of the associated background risks. The reason of this pervasive changes in the structure of the optimal international Equity OIV can be found in the very nature of Markov switching models used in asset management (see e.g., Guidolin and Timmermann, 2007): because the predicted probabilities of the bull and bear regimes converge to the steady-state, ergodic probabilities of the states as H grows, and such probabilities eventually reflect the overall frequency with which risk in the data is represented by regime shifts, in addition to the standard continuous diffusion (here, Gaussian component), it is possible that assets that represent excellent hedges of adverse regime changes over the short-horizon, may instead turn into riskier assets over longer planning horizons. Equivalently, under MS asset allocation, it is possible for optimal portfolio shares to display quite complex patterns as a function of H and our current application seems to offer such an example.[23]

5.3. *Realized Recursive Portfolio Performance*

Table 11 reports realized OOS Sharpe ratios for the international equity component of the recursive optimal portfolios examined in Section 5.1. Also here the back-testing period is 2002:01-2009:12 which

[23] Results have also been tabulated and examined when no short sale constraints are imposed in the exercise, and the findings are similar to the ones reported above. These are available upon request from the Authors.

includes two difficult periods for international stock markets, 2002 and 2008-2009, and also the alleged bubbly/euphoric 2005-2007 interval.[24] Once more, but using very different data, we ask whether an OIV ought to leave on the table a large portion of the realized Sharpe ratio potentially available because the workers investing through the OIV perceive hedging needs that may cause a structural deviation of their portfolio weights from the case of no background risk.

Table 11 shows that especially for intermediate and long investment horizons, the highest realized Sharpe ratios reward OIV strategies that take bull and bear regimes into account. In fact, this applies even when no labor income risk, or an equally weighted average of all such risks are taken into account. The results on realized, OOS 5-year performance are in fact truly impressive: (12) outperforms the IID benchmark in 38 cases out of 39, and hence independently of the assumed risk aversion coefficient. Interestingly, the best Sharpe ratios in Table 12 are considerably lower than those commented for Table 6. For instance, in the absence of labor income risk, for $\lambda = 1$ and $H = 12$ months the best achievable Sharpe ratio is 0.25 for the international asset menu vs. 0.40 for the sectorial menu in Table 6; when labor income risk is factored in, the best performing OIV in Table 12 yields a Sharpe ratio of 0.26 vs. 0.61 in Table 6.[25] One can summarize the size of the realized performance gains obtainable when moving from the Gaussian IID benchmark to the MS case as ranging from -0.05 to 0.04 (0.01 to 0.07) (as risk aversion increases) when $H = 1$ ($H = 12$) month and from 0.02 to 0.03 (with a peak at $\lambda = 1$) when $H = 60$. These are of course moderate improvements in absolute terms, but they become rather sizeable when one considers that the highest realized Sharpe ratio in Table 11 is indeed 0.26.

Table 12 reports results that—although much less striking—echo some of the patterns already found in Table 8: in realized OOS terms, we cannot even assume that building OIVs that implement bull and bear-sensitive portfolio strategies will lead to a net performance loss with respect to the case in which labor income risks are simply ignored.[26] In particular, highly risk averse workers with a short horizon will in fact benefit in net terms from bending their pension funds management to also hedge sectorial risks.[27] For instance, for $\lambda = 2$ and $H = 12$, the average OIV records a realized Sharpe ratio increase of 0.13 vs. the no background risk case, even if regimes are taken into account; the same score is 0.12 when $\lambda = 1$ and $H = 1$, and 0.04 when $\lambda = 1$ and $H = 12$. However, although a change in Sharpe ratios of 0.12-0.13 is in no way negligible when the highest achievable ratio is 0.26, the effects are more modest and also generally zero or slightly negative for truly long horizons. Further, as already anticipated in Section 5.1, this is due to the large number of estimated simultaneous correlation coefficients between labor income growth and international stock returns which are negative in the bear regime. It is also rational to expect that this own-risk diversification effect may be stronger for more risk-averse investors

[24]The table concerns the case in which short-sale constraints are imposed. For ease of consultation, in the table we have boldfaced—for each combination of λ and H—the highest realized Sharpe ratio across the two econometric models already featured in Figure 3.

[25]Similarly the 1/N strategy also generates lower Sharpe ratios: 0.19 vs. 0.49 ($H = 1$), 0.21 vs. 0.38 ($H = 12$) and 0.07 vs. 013 ($H = 60$).

[26]Conversely, a passive strategy that ignores predictability implies a uniform realized loss of performance between -0.001 and -0.058, which is what one would expect ex-ante, in in-sample terms.

[27]For the MS model, in 30 cases (OIVs) out of a total of 99 (11 OIVs $\times$ 3 risk aversion coefficients $\times$ 3 horizons), we find that OIVs out-perform the case in which no hedging of labor income risk is presented.

and for short-term planning horizons which is exactly what Table 12 reveals.

In additional unreported tabulation exercises (available upon request), we have performed the recursive OOS calculations afresh with reference to the case in which short-sales are admitted so that the formulas in (7) are directly used. Elaborations of these results to address the questions of interest reveal findings that are qualitatively similar to Tables 11 and 12 although also in this case sometimes weaker. For instance, although it still occurs that OIVs built taking bull and bear dynamics into account may improve realized performance vs. the case of no background risks, this finding is now possible but not dominant and on average the spread produced by the OIVs tends to be smaller. For instance, in the case of $H = 12$ we find that the average loss in realized Sharpe ratio due to the fact that labor income risk is taken into account is 0.01 for $\lambda = 0.5$, -0.07 (it is a gain) for $\lambda = 1$, and -0.31 (a large gain) for $\lambda = 2$.

6. **Robustness Checks**

To examine whether our findings are data- or sample-specific we repeat (and, to some extent) generalize the exercises in Sections 4 and 5 using from a UK perspective using the data outlined in Section 3. The underlying idea is that if OIVs that condition on the market regimes represent a viable approach to occupational-linked portfolio choices, in the sense that these come at little or no performance costs, this result should hold more generally than with the two data sets analyzed so far in our paper. Although all the checks performed in this Section concern UK data, they can be sub-divided under three key headers. First, we simply repeat the calculations supporting Section 4 on similar, British sectorial data. This is a case in which $N = M$ so that the asset menu has a structure that is symmetric to the sectorial, background risk framework that allows us to characterize OIVs. Second, we focus on reporting in a specific way detailed results on a UK sectorial exercise when short sales are allowed. While we have expressed a few occasional comments on this case in Sections 4 and 5, we take the opportunity here to report full results. Third, in parallel to Section 5 we also illustrate the realized performances of an international equity diversification exercise in a British perspective. Although Sections 6.1-6.3 are based on a limited number of tables and figures, full tabulations and detailed pictures remain available from the Authors upon request.

6.1. *UK Data: Baseline Sectorial Allocation*

Because with UK data—on $N = M = 7$ sectors—we have available only a shorter 2000:01-2010:12 monthly data sample, our econometric estimates were implemented differently from Section 4. First of all, we focus our attention only on the Gaussian IID model and a two-state Markov switching model. Second, instead of a estimating a unique MS model, we have estimated 7 different MS models, each of them including stock returns from each of the 7 sectors, augmented by data on labor income growth from one of the sectors at the time.[28] On the one hand, this way of proceeding mimics the logic of imposing

[28]Clearly, also the Gaussian IID model could have been implemented this way, but given its simple structure based on sample mean and variance parameters only, this would make no difference to our results.

restrictions on the structure of the regime-dependent covariance matrices already discussed in Sections 4 and 5. On the other hand, and differently from before, it implies that in practice parameter estimates for 7 different two-state Markov chain process will become available: if such Markov chain parameter estimates are not completely consistent as far as the dynamics of stock returns is concerned, this may imply some issues of parameter consistency and—eventually—of positive definiteness of the resulting forecasts of the covariance matrix. Third, just because the sample we have is relatively short, in this case we have considered only two horizons, $H = 1$ and 12 months.

The full sample ML/EM estimates from the MS model are reported in Table 13 (the plots of the smoothed probabilities of the bull and bear states obtained as averages over the 7 estimated MS models are available upon request). The bear state captures well known periods across the decade, including the impact of the 9/11 terrorist attack in 2001, the bursting of the internet bubble in 2002-2003 and the impact of the global financial crisis in 2008 followed by a bear/recession state in 2009-2010. However given the nature and drivers behind these bear states, they have an asymmetric impact across sectors. Hence in contrast to the US findings the mean sector return is negative in only 3 out of 7 sectors; for a further 3 sectors the bear mean returns are lower than those witnessed during bull states, while the construction sector provides for higher average returns during the bear state than in the bull state. Though noticeably volatility is always higher during the bear state. Table 14 reports the sector equity return correlations in the different states, the bear state correlations above the diagonal are typically much higher than the bull state correlations below the diagonal. This is entirely consistent with expectations, the prior literature and our US results that correlations tend to increase during bear markets. Table 15 can be interpreted in the same manner as Table 4. While the estimated states are less persistent, again compensation growth and sector stock returns are typically negatively correlated during the bear state. Table 15 is also crucial because it shows how the 7 different two-state models described above relate to each other. Although some differences in the persistence of the Markov chain and hence in average durations may be detected, all the regimes are persistent and characterize between 50 and 70% of the sample (in the case of bear regime), while the linear, single-state model was always rejected by both information criteria and using likelihood ratio tests that adjust for nuisance parameter problems.

The optimal, constrained (under no short-sales) portfolio weights (tabulations of summary statistics and pie charts are available upon request) reveal that when an investor has no background risk, the portfolio composition is similar whether the investor elects no predictability or non-linear predictability. Such optimal composition is heavily tilted (as odd as this may be) towards agriculture, forestry & fishing (50%), and mining & quarrying (28%). This may reflect the fact that the UK economy is now so heavily tilted towards finance and banking, general services and manufacturing, that activities in the primary sector do offer considerable hedging gains. However once employability is accounted for and either an average risk or sector specific labor income risk enter the portfolio choice problem, the asset allocation implied by the MS model differs quite markedly from that of the Gaussian IID framework. In 6 out of 8 cases the no predictability benchmark produces an allocation that places more than 50% of wealth in an individual sector (industrials) whereas the MS model suggests a loading in excess of 40% on only 3 occasions, and this always occurs by increasing the load onto financial stocks.

In terms of performance, following the patterns of the US results reported earlier, Table 16 reports the realized OOS Sharpe ratios when the portfolios are constrained, with the MS model producing superior Sharpe ratios in 40 out of $54 = 9 \times 3 \times 2$ cases.[29] This superior performance appears robust across horizons and levels of risk aversion. For most employees taking account of your labor income risk yields performance gains (see Table 17) and not losses, though there appears no such benefit for investors with low or medium levels of risk aversion working in the retail, trade and repairs or financial sectors. In addition the benefit accruing to accounting for background risk appears largely independent of an investor's assumption regarding predictability. However the benefits of accounting for predictability are highlighted by computing the change in Sharpe ratio that results from shifting to the MS model from simply adopting the no predictability benchmark. In 39 cases the investor benefits if she decides to take non-linear predictability into account (detailed results are available upon request).

6.2. *UK Data: Sectorial Allocation with Short Sale Possibilities*

Similarly to the US exercise we also perform the same calculations as above but with no short sale constraints imposed on the portfolio problem.[30] While ignoring labor income risks leads by and large to concluding that realized Sharpe ratios are higher when Markov switching dynamics is taken into account, when hedging background risk becomes a factor, the overall picture becomes more nuanced. For short term horizons (for which the UK results appear to be more reliable, given the short OOS period), we find again that on average across OIVs, taking labor income risks into account would come at no cost in terms of realized Sharpe ratios. However, such nil or negative sacrifice of realized performance to hedge labor income risks disappears when one considers longer investment horizons. Given the short sample employed in this robustness check, we trust that these results should be further investigated using longer time series, more representative of the actual sequencing of bull and bear states in the UK.

6.3. *UK Data: International Diversification*

Finally, we consider a UK employee who wishes to diversify internationally also to hedge her background risk related to her sectorial employment. Unreported tabulations of summary statistics for the optimal composition of portfolios (potentially) comprising of investments in UK, Japan, Asia excluding Japan, Europe excluding UK and North America equity returns for short and intermediate horizons, three levels of risk aversion, differing background risk and whether the investor adopts a Gaussian IID or a MS model reveal that, consistent with our previous findings, the choice of econometric model leads to substantially different optimal portfolio outcomes. Typically the level of observed home bias (weight on UK equity) is lower and the weight placed in North America is much higher under a MS model than under a model

[29] These realized performances are computed with reference to the OOS period 2007:01-2010:12, for a total of $48-H$ possible performances. In this perspective it is vital to also include 2010 in our data to balance the OOS experiment to include the 2007 and 2010 bull markets besides the Great Financial Crisis of 2008-2009.

[30] Results available upon request from the Authors.

that ignores predictability.

Table 18 reports realized Sharpe ratios from the typical exercise with constrained weights. Once more the best performing model tends to be MS over the Gaussian IID case: the regime switching framework produces the best realized OOS Sharpe Ratio in 38 of the 54 cases, though there is some evidence that an average employee is better off ignoring predictability. Moreover, the Sharpe ratio report in this table tend to be small compared to those seen in the rest of the paper, and this is attributable to the fact that most of our OOS period in fact coincides with the worldwide financial crisis and its aftershocks. However, the general principle that structuring OIVs around the detection and the forecasting of bull and bear regimes holds in this most recent and difficult period as well.

7. **Conclusions**

That optimal portfolio choices ought to depend on the structure of an investor's background risks—such as the correlation between her non-capital income and the returns of the assets in her investment menu—is a result as old as modern finance theory itself. This implies that the architecture of financial markets should be based not on investment vehicles (such as mutual or hedge funds) that can be distinguished because of either their specialty asset class(es) or their investment styles, but on occupational vehicles (such as sector-specific pension funds) that should apply strategies that condition on the average dynamics of compensations typical of each sector and occupation. This is made all the more important by massive evidence of regimes and parameter instability in the relationships between financial returns and underlying economic conditions, to also include the rate of growth of sectorial compensations and wages. However, it is also commonly thought that this capability to hedge background risks ought to come at some cost, in terms of a reduced investment performance. Although ex-ante this point is rather obvious, in the presence of random returns and model misspecification, there is no guarantee that an expected loss may actually materialize ex-post, in recursive realized OOS terms. The objective of our paper was to test whether the principle that setting up occupational investment vehicles is costly in terms of realized performances also holds ex-post. Our main result is striking: such a cost is generally small and—especially for highly risk averse and medium term strategies that take the existence of regimes into account—may often be negative, which implies that OIVs may end up yielding a higher realized performance than strategies that apply unconditionally to all investors, disregarding their background risks.

There are a number of obvious directions in which this paper may be usefully extended. First, our evidence in this paper has been based on data for two countries (US and UK) and two alternative asset menus (sectorial domestic, and international equities) for each of the two countries. More extensive evidence for more countries, more asset menus (to include not only equities but also bonds) and longer sample periods is certainly needed, although our initial robustness checks have been encouraging. Second, although we feel that the evidence of regimes, instability and nonlinearities is rather overwhelming, it is a fact that our effort has been based on a rather simplistic two-state MS model. It would be interesting to see how our striking findings in this paper change as the model is further refined and improved. Third, our allocation framework is based on a simple mean-variance optimization (implying that performances ought to be ranked based on their Sharpe ratios) is a natural starting point and yet it would be interesting to check whether our results hold when portfolio weights are computed from more realistic and time-consistent preferences, starting from classical power, constant relative risk aversion preferences.

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Table 1

Descriptive Statistics for Stock Return and Workers' Compensation Growth

Stock Return and Risk-Free Rate Data

U.S. Industry Portfolios (1990-2009)	Mean	Std. Dev.
Non Durables	0.879	3.970
Durables	0.673	7.013
Manufacturing	0.995	5.402
Energy	1.028	5.257
Chemical	0.883	4.410
Business Equipment	1.117	7.704
Telecommunications	0.496	5.467
Utilities	0.773	4.202
Shops and Retail	0.859	4.822
Health	0.935	4.638
Money and Finance	0.889	5.822

MSCI 6 International Ptfs. (1990-2009)	Mean	Std. Dev.
US Local Returns	0.799	4.337
Canada Local Returns	0.665	4.558
UK Local Returns	0.722	4.260
Japan Local Returns	-0.166	5.831
Asia ex Japan Local Returns	0.598	5.653
Europe ex UK Local Returns	0.665	5.193

U.S. 1-month T-Bill Rate (1990-2009)	Mean	Std. Dev.
	0.933	5.792

U.K. Sectoral Portfolios (2000-2010)	Mean	Std. Dev.
Industrials	1.179	7.273
Agriculture, Forestry and Fishing	0.957	4.125
Mining and Quarrying	1.665	6.076
Electricity, Gas and Water Supply	0.669	6.455
Constructions	0.493	4.717
Retail Trade and Repairs	0.307	5.829
Financial Intermediation	0.319	6.630

MSCI 5 International Ptfs. (2000-2010)	Mean	Std. Dev.
North America Local Returns	0.012	4.494
UK Local Returns	0.470	4.395
Japan Local Returns	-0.168	5.207
Asia ex Japan Local Returns	0.436	5.040
Europe ex UK Local Returns	0.214	5.399

U.K. 1-month T-Bill Rate (2000-2010)	Mean	Std. Dev.
	0.346	0.120

Employee Compensation Growth Data

U.S. Industry Wage Growth Rates (1990-2009)	Mean	Std. Dev.
Non Durables	0.923	3.921
Durables	0.692	7.021
Manufacturing	1.023	5.396
Energy	1.049	5.257
Chemical	0.920	4.381
Business Equipment	1.127	7.719
Telecommunications	0.553	5.407
Utilities	0.799	4.192
Shops and Retail	0.888	4.811
Health	0.970	4.616
Money and Finance	0.933	5.792

U.K. Sectoral Wage Growth Rates (2000-2010)	Mean	Std. Dev.
Industrials	0.505	3.827
Agriculture, Forestry and Fishing	0.474	3.647
Mining and Quarrying	1.270	9.166
Electricity, Gas and Water Supply	0.463	3.158
Constructions	0.384	2.095
Retail Trade and Repairs	0.422	2.522
Financial Intermediation	0.373	1.033

Table 2

Two-State Markov Switching Estimates: U.S. Sector Stock Return Estimates

The table reports the MLE/EM estimates from a two-state Markov switching model. The unconditional volatility is computed using the ergodic state probabilities implied by the model and according to the formula:

$$\sigma^{erg} = \sqrt{\pi^{erg}\sigma^2_{bear} + (1-\pi^{erg})\sigma^2_{bull} + \pi^{erg}(1-\pi^{erg})(\mu_{bull} - \mu_{bearl})^2} \ ,$$

The Sharpe ratios are computed using a regime-specific riskless interest rate (1-month T-bill yield) computed as the state-specific average of the available data over the sample period 1990:02 – 2009:12. Months in which the smoothed (full-sample) probability of a bear regime exceeds or is equal to 0.5 are classified as bear states; all other months in the sample are classified as bull states.

		Mean Return	Regime-Specific Volatility of Returns	Unconditional (Long-Run) Volatility of Returns	Regime-Specific Sharpe Ratio	Unconditional (Long-Run) Sharpe Ratio
Non-Durables	Bear	-0.095	4.990	3.907	-0.074	0.158
	Bull	1.280	3.383		0.284	
Durables	Bear	-0.747	10.539	6.988	-0.097	0.056
	Bull	1.198	5.131		0.171	
Manufacturing	Bear	-0.721	7.989	5.370	-0.124	0.134
	Bull	1.635	3.914		0.336	
Energy	Bear	-0.775	6.330	5.240	-0.166	0.143
	Bull	1.691	4.640		0.295	
Chemicals	Bear	-0.763	5.555	4.365	-0.186	0.142
	Bull	1.511	3.694		0.322	
Business Eqpm.	Bear	-0.499	12.071	7.679	-0.064	0.108
	Bull	1.698	5.265		0.262	
Telecommunic.	Bear	-1.265	8.162	5.380	-0.188	0.047
	Bull	1.192	3.791		0.230	
Utilities	Bear	-0.581	5.788	4.175	-0.148	0.119
	Bull	1.284	3.313		0.291	
Shops & Retail	Bear	-0.170	6.353	4.793	-0.070	0.122
	Bull	1.260	4.053		0.232	
Health	Bear	0.098	5.622	4.602	-0.031	0.145
	Bull	1.276	4.148		0.230	
Money & Finance	Bear	-0.572	8.414	5.766	-0.100	0.110
	Bull	1.463	4.382		0.261	

Table 3

Two-State Markov Switching Estimates: Sector Stock Return Correlations

The tables reports the MLE/EM estimates from a two-state Markov switching model. In the table, boldfaced coefficients are statistically significant with a p-value of 0.05 or lower.

	NoDur	Durbl	Manuf	Enrgy	Chems	BusEq	Telcm	Utils	Shops	Health	Money
NoDur		**0.485**	**0.659**	**0.252**	**0.678**	**0.564**	**0.614**	**0.528**	**0.666**	**0.709**	**0.643**
Durbl	**0.569**		**0.782**	**0.342**	**0.660**	**0.620**	**0.548**	**0.288**	**0.630**	**0.381**	**0.647**
Manuf	**0.673**	**0.848**		**0.498**	**0.817**	**0.765**	**0.631**	**0.343**	**0.720**	**0.546**	**0.715**
Enrgy	**0.537**	**0.423**	**0.640**		**0.442**	**0.314**	**0.306**	**0.412**	0.170	0.158	**0.273**
Chems	**0.806**	**0.679**	**0.782**	**0.509**		**0.608**	**0.533**	**0.374**	**0.637**	**0.608**	**0.666**
BusEq	**0.259**	**0.554**	**0.672**	**0.336**	**0.335**		**0.488**	0.222	**0.682**	**0.530**	**0.607**
Telcm	**0.421**	**0.592**	**0.623**	**0.346**	**0.387**	**0.743**		**0.595**	**0.519**	**0.492**	**0.597**
Utils	**0.443**	**0.328**	**0.436**	**0.745**	**0.417**	0.069	0.113		**0.249**	**0.331**	**0.419**
Shops	**0.702**	**0.741**	**0.806**	**0.458**	**0.658**	**0.637**	**0.714**	0.246		**0.567**	**0.706**
Health	**0.617**	**0.371**	**0.482**	**0.428**	**0.524**	**0.435**	**0.478**	**0.435**	**0.433**		**0.589**
Money	**0.809**	**0.758**	**0.790**	**0.529**	**0.761**	**0.466**	**0.579**	**0.421**	**0.771**	**0.567**	

Bull State Estimates

Bear State Estimates

Table 4

Two-State Markov Switching Estimates: Sector Compensation Growth Estimates and U.S. Industry Stock Returns

The table reports the MLE/EM estimates from a two-state Markov switching model. The HQ criterion is an information criterion that trades-off in-sample fit with model parsimony. In the table, the regime-specific means and standard deviations are boldfaced when they turned out to be statistically significant on the basis of a likelihood ratio test of the equality restriction in estimation. When both means and variances are statistically different across regimes and this can be only detected using a joint test, both mean and variance coefficients have been boldfaced.

Compensation Growth		Wage Mean	Wage St. dev.	Contemporaneous Correlation with Sectoral Stock Returns										
				NoDur	Durbl	Manuf	Enrgy	Chems	BusEq	Telcm	Utils	Shops	Health	Money
Non-Durables	Bear	**0.286**	0.472	-0.177**	-0.110*	-0.137**	-0.125*	-0.180***	-0.055	-0.018	-0.103	-0.060	-0.063	-0.103
	Bull	**0.232**	0.448	-0.027	0.007	0.073	0.016	0.029	-0.029	0.107*	0.037	-0.049	0.033	0.045
Durables	Bear	0.247	**1.978**	-0.110*	-0.167**	-0.076	0.151**	-0.014	-0.103*	-0.080	0.242***	-0.105*	-0.096	-0.175**
	Bull	0.217	**1.622**	0.062	0.044	-0.003	-0.004	-0.010	0.028	0.062	0.043	0.007	0.029	-0.035
Manufacturing	Bear	0.264	0.410	-0.066	-0.085	-0.047	0.001	-0.028	-0.150**	0.021	0.019	0.025	0.056	0.021
	Bull	0.224	0.416	-0.015	-0.032	0.031	0.073	0.032	-0.061	0.096	0.092	-0.075	0.022	-0.012
Energy	Bear	**0.128**	0.872	0.006	0.027	-0.005	-0.026	0.058	-0.009	0.184***	0.089	0.130**	0.056	0.006
	Bull	**0.266**	0.919	-0.019	0.009	0.033	-0.052	0.040	-0.009	0.028	0.023	-0.053	0.064	-0.016
Chemicals	Bear	**0.237**	**0.665**	-0.216***	-0.117**	-0.183***	-0.180***	-0.193***	-0.169**	-0.113**	-0.174***	-0.127**	-0.086	-0.104
	Bull	**0.204**	**0.595**	-0.044	-0.029	0.002	-0.035	0.035	-0.034	0.005	-0.032	-0.063	0.012	-0.030
Business Eqpm.	Bear	**0.411**	0.644	-0.144**	-0.072	-0.241***	-0.194***	-0.197	-0.244***	-0.086	-0.073	-0.110*	-0.106	-0.141**
	Bull	**0.312**	0.646	-0.012	-0.051	-0.018	0.015	0.027	-0.090	-0.021	0.016	-0.046	0.037	0.010
Telecommunic.	Bear	0.297	0.685	-0.134**	-0.056	-0.030	0.061	-0.058	0.056	-0.068	0.004	-0.094	-0.034	-0.134**
	Bull	0.267	0.640	-0.120**	-0.157**	-0.123**	-0.046	-0.179***	-0.028	-0.076	-0.081	-0.067	-0.025	-0.049
Utilities	Bear	0.223	**0.801**	-0.118*	-0.114*	-0.176**	0.019	-0.258***	-0.131**	-0.144**	0.002	-0.074	-0.163**	-0.177**
	Bull	0.246	**0.636**	-0.062	-0.073	-0.015	-0.028	0.010	0.023	0.012	-0.047	-0.021	0.033	-0.049
Shops & Retail	Bear	0.236	0.633	-0.325***	-0.063	-0.269***	-0.121*	-0.333***	-0.181***	-0.120*	-0.000	-0.283***	-0.140**	-0.307**
	Bull	0.239	0.648	-0.122*	-0.050	-0.066	0.000	-0.044	0.004	-0.041	-0.123*	-0.054	-0.026	-0.025
Health	Bear	**0.361**	0.310	-0.060	0.061	-0.100	-0.240***	-0.045	-0.135**	0.089	-0.127**	0.034	-0.017	0.067
	Bull	**0.292**	0.305	0.016	-0.005	0.070	0.081	0.113*	-0.009	0.069	0.004	-0.039	0.035	0.021
Money & Finance	Bear	0.291	**0.521**	-0.191***	-0.098	-0.275***	-0.029	-0.141**	-0.408***	-0.167**	0.058	-0.290***	-0.240***	-0.202***
	Bull	0.333	**0.624**	0.031	-0.048	0.003	-0.026	0.018	0.053	0.008	-0.048	0.070	0.076	0.003

* Significant at 10% or lower; ** significant at 5% or lower; *** significant at 1% or lower.

Table 5

Realized, Recursive Out-of-Sample Sharpe Ratios of Constrained Portfolios Under Alternative Background Risk Models

The table reports realized, recursive, out-of-sample Sharpe ratios for mean-variance optimizing portfolios across 11 U.S. sectors as a function of the background risk model and the econometric model used to capture any predictability in the dynamic relationship between employee total compensation and stock returns. Three alternative models are considered: Gaussian IID (no predictability), a Gaussian VAR(1) in which past stock returns and compensation growth rates may forecast subsequent asset returns, a two-state Markov switching model in which both stock returns and compensation growth rates affect the inference and the predictions of the future regime dynamics. The calculations are performed with reference to the period Jan. 2002 – Dec. 2009, assuming three alternative risk aversion levels and three horizons. The column "No" refers to the case in which no background risk is taken into account or, equivalently, when the mean-variance portfolio optimizer is not to be employed. Boldfaced Sharpe ratios are the best within a given background risk framework (i.e., for a selected OPF).

Gaussian IID Model (No Predictability)

Risk Aversion	No	Avg.	NoDur	Durbl	Manuf	Enrgy	Chems	BusEq	Telcm	Utils	Shops	Hlth	Money
Short Investment Horizon (1 month)													
High	0.446	0.440	0.179	0.168	0.176	0.187	0.178	0.175	0.179	0.157	0.172	0.173	0.160
Medium	0.446	0.417	0.218	0.179	0.200	0.258	0.209	0.194	0.228	0.126	0.218	0.191	0.149
Low	0.446	0.407	0.257	**0.205**	0.215	0.311	0.246	0.220	0.295	0.138	0.270	0.211	0.159
Intermediate Investment Horizon (1 year)													
High	0.313	0.305	0.197	0.214	0.199	0.187	0.186	0.219	0.196	0.205	0.236	0.219	0.225
Medium	0.313	0.277	0.153	**0.217**	0.162	0.113	0.118	0.227	0.146	0.176	0.302	0.224	0.265
Low	0.313	0.279	0.143	**0.235**	0.138	0.109	0.104	0.236	0.128	0.185	0.355	0.230	**0.301**
Long Investment Horizon (5 years)													
High	**0.120**	**0.112**	0.014	0.015	0.014	0.015	0.013	0.016	0.014	0.014	0.017	0.016	0.017
Medium	**0.120**	**0.073**	0.012	0.015	0.012	0.013	0.009	0.016	0.013	0.011	0.019	0.016	0.021
Low	**0.120**	0.053	0.012	0.016	0.011	0.012	0.008	0.016	0.014	0.011	0.020	0.015	0.027

VAR Model (Linear Predictability)

Risk Aversion	No	Avg.	NoDur	Durbl	Manuf	Enrgy	Chems	BusEq	Telcm	Utils	Shops	Hlth	Money
Short Investment Horizon (1 month)													
High	**0.455**	**0.477**	0.121	0.163	0.198	0.256	0.142	0.159	0.169	0.187	0.191	0.131	0.185
Medium	**0.467**	0.361	0.115	0.110	0.197	0.267	0.224	0.161	0.165	0.185	0.194	0.129	0.189
Low	**0.455**	0.456	0.110	0.084	0.197	0.272	0.149	0.165	0.156	0.185	0.199	0.125	0.193
Intermediate Investment Horizon (1 year)													
High	**0.409**	**0.438**	0.218	0.136	0.090	0.066	0.170	0.137	0.348	0.164	0.147	0.244	0.085
Medium	**0.395**	**0.345**	0.292	0.156	0.134	0.078	0.267	0.199	**1.253**	0.257	0.258	0.347	0.184
Low	**0.411**	**0.326**	0.228	0.181	0.149	0.116	0.317	0.186	**1.405**	0.235	0.288	0.333	0.281
Long Investment Horizon (5 years)													
High	0.106	0.070	**0.045**	**0.038**	0.039	0.037	0.038	0.038	0.040	0.037	0.035	0.038	0.036
Medium	0.109	0.090	0.052	**0.031**	0.032	0.034	0.040	0.036	0.049	**0.038**	0.030	0.046	**0.036**
Low	0.114	**0.094**	0.039	**0.018**	0.037	0.033	0.040	0.035	0.057	0.039	0.029	0.049	**0.036**

Markov Switching Model (Nonlinear Predictability)

Risk Aversion	No	Avg.	NoDur	Durbl	Manuf	Enrgy	Chems	BusEq	Telcm	Utils	Shops	Hlth	Money
Short Investment Horizon (1 month)													
High	0.392	0.344	**0.673**	**0.640**	**0.619**	**0.641**	**0.610**	**0.595**	**0.596**	**0.487**	**0.607**	**0.617**	**0.645**
Medium	0.424	**0.426**	**0.619**	**0.395**	**0.591**	**0.633**	**0.578**	**0.419**	**0.629**	**0.533**	**0.569**	**0.575**	**0.530**
Low	0.489	**0.475**	**0.524**	0.112	**0.513**	**0.568**	**0.482**	**0.429**	**0.600**	**0.427**	**0.612**	**0.585**	**0.414**
Intermediate Investment Horizon (1 year)													
High	0.341	0.315	**0.355**	**0.234**	**0.363**	**0.331**	**0.630**	**0.349**	**0.364**	**0.337**	**0.382**	**0.387**	**0.348**
Medium	0.328	0.285	**0.494**	0.041	**0.465**	**0.605**	**0.488**	**0.432**	0.511	**0.314**	**0.428**	**0.481**	**0.336**
Low	0.362	0.098	**0.374**	0.013	**0.323**	**0.592**	**0.343**	**0.485**	0.442	**0.261**	**0.489**	**0.496**	0.284
Long Investment Horizon (5 years)													
High	0.072	0.054	0.033	0.003	**0.088**	**0.140**	**0.062**	**0.052**	**0.101**	**0.047**	**0.138**	**0.121**	**0.100**
Medium	0.108	0.024	**0.101**	0.000	**0.089**	**0.166**	**0.079**	**0.103**	**0.134**	0.037	**0.147**	**0.152**	0.018
Low	0.059	0.008	**0.093**	0.000	**0.048**	**0.163**	**0.078**	**0.112**	**0.127**	**0.045**	**0.157**	**0.155**	0.023

Table 6

Out-of-Sample Sharpe Ratios Gain from Taking Predictability into Account: Constrained Portfolios

The table reports realized, recursive, out-of-sample increases in Sharpe ratios vs. the case of no predictability (i.e., when the investor performs mean-variance asset allocation under a simple Gaussian IID model) across 11 U.S. sectors as a function of the background risk model and the econometric model used to capture any predictability in the dynamic relationship between employee total compensation and stock returns. The calculations are performed with reference to the period Jan. 2002 – Dec. 2009, assuming three alternative risk aversion levels and three horizons. The column "No" refers to the case in which no background risk is taken into account. Boldfaced Sharpe ratios indicate a Sharpe ratio gain.

VAR Model (Linear Predictability)

Risk Aversion	No	Avg.	NoDur	Durbl	Manuf	Enrgy	Chems	BusEq	Telcm	Utils	Shops	Hlth	Money
Short Investment Horizon (1 month)													
High	**0.009**	**0.037**	-0.058	-0.005	**0.022**	**0.069**	-0.037	-0.016	-0.009	**0.031**	**0.020**	-0.041	**0.026**
Medium	**0.021**	-0.057	-0.103	-0.069	-0.003	**0.009**	**0.015**	-0.032	-0.063	**0.059**	-0.024	-0.062	**0.040**
Low	**0.009**	**0.049**	-0.147	-0.120	-0.018	-0.038	-0.097	-0.055	-0.139	0.047	-0.071	-0.086	**0.035**
Intermediate Investment Horizon (1 year)													
High	**0.095**	**0.134**	**0.021**	-0.078	-0.109	-0.121	-0.016	-0.082	**0.152**	-0.041	-0.090	**0.025**	-0.141
Medium	**0.082**	**0.068**	**0.139**	-0.061	-0.029	-0.035	**0.149**	-0.028	**1.106**	**0.081**	-0.044	**0.123**	-0.081
Low	**0.098**	**0.047**	**0.085**	-0.054	**0.011**	**0.007**	**0.213**	-0.049	**1.277**	**0.050**	-0.067	**0.103**	-0.020
Long Investment Horizon (5 years)													
High	-0.014	-0.042	**0.031**	**0.023**	**0.024**	**0.022**	**0.025**	**0.022**	**0.027**	**0.023**	**0.018**	**0.022**	**0.019**
Medium	-0.011	**0.017**	**0.040**	**0.016**	**0.020**	**0.021**	**0.031**	**0.020**	**0.037**	**0.027**	**0.012**	**0.030**	**0.014**
Low	-0.006	**0.041**	**0.027**	**0.002**	**0.026**	**0.021**	**0.032**	**0.019**	**0.043**	**0.027**	**0.009**	**0.034**	**0.009**

Markov Switching Model (Nonlinear Predictability)

Risk Aversion	No	Avg.	NoDur	Durbl	Manuf	Enrgy	Chems	BusEq	Telcm	Utils	Shops	Hlth	Money
Short Investment Horizon (1 month)													
High	-0.053	-0.096	**0.493**	**0.472**	**0.443**	**0.453**	**0.432**	**0.420**	**0.418**	**0.330**	**0.435**	**0.444**	**0.485**
Medium	-0.021	**0.009**	**0.401**	**0.217**	**0.391**	**0.375**	**0.369**	**0.225**	**0.401**	**0.407**	**0.351**	**0.383**	**0.381**
Low	**0.044**	**0.068**	**0.267**	-0.093	**0.298**	**0.257**	**0.236**	**0.209**	**0.305**	**0.290**	**0.342**	**0.374**	**0.256**
Intermediate Investment Horizon (1 year)													
High	**0.028**	**0.011**	**0.158**	**0.020**	**0.165**	**0.144**	**0.444**	**0.129**	**0.168**	**0.132**	**0.146**	**0.168**	**0.122**
Medium	**0.014**	**0.008**	**0.341**	-0.176	**0.302**	**0.492**	**0.370**	**0.205**	**0.365**	**0.139**	**0.126**	**0.257**	**0.072**
Low	**0.049**	-0.181	**0.231**	-0.222	**0.185**	**0.484**	**0.238**	**0.250**	**0.314**	**0.076**	**0.134**	**0.266**	-0.017
Long Investment Horizon (5 years)													
High	-0.049	-0.058	**0.019**	-0.013	**0.074**	**0.126**	**0.048**	**0.036**	**0.087**	**0.033**	**0.122**	**0.105**	**0.084**
Medium	-0.012	-0.050	**0.088**	-0.015	**0.078**	**0.154**	**0.070**	**0.088**	**0.122**	**0.026**	**0.128**	**0.136**	-0.004
Low	-0.061	-0.045	**0.080**	-0.016	**0.037**	**0.150**	**0.070**	**0.097**	**0.113**	**0.034**	**0.137**	**0.140**	-0.004

Table 7

Out-of-Sample Sharpe Ratios Loss from Background Risk Exposure: Constrained Portfolios

The table reports realized, recursive, out-of-sample declines in Sharpe ratios vs. the case of no background risk (i.e., when the investor is not employed) for mean-variance optimizing portfolios across 11 U.S. sectors as a function of the background risk model and the econometric model used to capture any predictability in the dynamic relationship between employee total compensation and stock returns. Three alternative models are considered: Gaussian IID, a Gaussian VAR(1), and a two-state Markov switching model. The calculations are performed with reference to the period Jan. 2002 – Dec. 2009, assuming three alternative risk aversion levels and three horizons. All Sharpe ratios are reported in annualized levels. Boldfaced Sharpe ratios indicate that the Sharpe ratio loss is negative, i.e., that an investor may gain in realized terms in spite of her taking into account of background risk.

Risk Aversion	NoDur	Durbl	Manuf	Enrgy	Chems	BusEq	Telcm	Utils	Shops	Hlth	Money
	Gaussian IID Model (No Predictability)										
Short Investment Horizon (1 month)											
High	0.267	0.278	0.269	0.258	0.267	0.271	0.267	0.289	0.274	0.273	0.286
Medium	0.228	0.267	0.245	0.188	0.236	0.252	0.217	0.320	0.228	0.255	0.296
Low	0.188	0.241	0.231	0.135	0.199	0.226	0.151	0.308	0.176	0.235	0.287
Intermediate Investment Horizon (1 year)											
High	0.116	0.099	0.114	0.127	0.127	0.094	0.118	0.108	0.077	0.094	0.088
Medium	0.160	0.096	0.151	0.200	0.196	0.087	0.167	0.138	0.011	0.089	0.048
Low	0.170	0.078	0.176	0.205	0.209	0.077	0.185	0.128	**-0.042**	0.083	0.012
Long Investment Horizon (5 years)											
High	0.106	0.105	0.106	0.106	0.107	0.105	0.107	0.106	0.104	0.104	0.104
Medium	0.108	0.105	0.109	0.108	0.111	0.105	0.108	0.110	0.102	0.104	0.099
Low	0.108	0.104	0.110	0.108	0.112	0.105	0.107	0.109	0.100	0.105	0.094

Risk Aversion	NoDur	Durbl	Manuf	Enrgy	Chems	BusEq	Telcm	Utils	Shops	Hlth	Money
	VAR Model (Linear Predictability)										
Short Investment Horizon (1 month)											
High	0.324	0.283	0.247	0.189	0.304	0.287	0.276	0.259	0.254	0.315	0.260
Medium	0.331	0.336	0.249	0.179	0.221	0.285	0.280	0.260	0.252	0.317	0.257
Low	0.335	0.361	0.249	0.173	0.297	0.281	0.289	0.261	0.246	0.321	0.252
Intermediate Investment Horizon (1 year)											
High	0.095	0.177	0.224	0.248	0.143	0.176	**-0.034**	0.149	0.167	0.069	0.229
Medium	0.021	0.157	0.180	0.235	0.046	0.114	**-0.940**	0.057	0.055	**-0.034**	0.129
Low	0.086	0.133	0.165	0.198	**-0.004**	0.127	**-1.092**	0.078	0.026	**-0.020**	0.032
Long Investment Horizon (5 years)											
High	0.075	0.082	0.082	0.083	0.082	0.083	0.080	0.084	0.086	0.082	0.084
Medium	0.068	0.089	0.089	0.087	0.080	0.085	0.071	0.082	0.090	0.074	0.085
Low	0.081	0.102	0.083	0.087	0.080	0.086	0.063	0.082	0.091	0.072	0.084

Risk Aversion	NoDur	Durbl	Manuf	Enrgy	Chems	BusEq	Telcm	Utils	Shops	Hlth	Money
	Markov Switching Model (Nonlinear Predictability)										
Short Investment Horizon (1 month)											
High	**-0.280**	**-0.247**	**-0.227**	**-0.248**	**-0.218**	**-0.202**	**-0.204**	**-0.095**	**-0.215**	**-0.225**	**-0.252**
Medium	**-0.195**	**0.029**	**-0.167**	**-0.209**	**-0.153**	**0.006**	**-0.205**	**-0.109**	**-0.145**	**-0.150**	**-0.106**
Low	**-0.035**	0.378	**-0.023**	**-0.079**	0.007	0.060	**-0.111**	0.062	**-0.123**	**-0.095**	0.075
Intermediate Investment Horizon (1 year)											
High	**-0.015**	0.106	**-0.023**	0.010	**-0.289**	**-0.008**	**-0.023**	0.004	**-0.041**	**-0.046**	**-0.007**
Medium	**-0.166**	0.287	**-0.137**	**-0.278**	**-0.160**	**-0.105**	**-0.184**	0.014	**-0.100**	**-0.154**	**-0.009**
Low	**-0.011**	0.349	0.039	**-0.230**	0.020	**-0.123**	**-0.079**	0.101	**-0.127**	**-0.134**	0.079
Long Investment Horizon (5 years)											
High	0.038	0.069	**-0.016**	**-0.069**	0.010	0.020	**-0.029**	0.025	**-0.067**	**-0.049**	**-0.028**
Medium	0.007	0.108	0.019	**-0.058**	0.029	0.005	**-0.026**	0.072	**-0.039**	**-0.044**	0.091
Low	**-0.033**	0.059	0.012	**-0.103**	**-0.019**	**-0.053**	**-0.067**	0.014	**-0.098**	**-0.095**	0.037

Table 8

Two-State Markov Switching Estimates: MSCI Equity Index Local Return Estimates

The table reports the MLE/EM estimates from a two-state Markov switching model. The unconditional volatility is computed using the ergodic state probabilities implied by the model and according to the formula:

$$\sigma^{erg} = \sqrt{\pi^{erg}\sigma^2_{bear} + (1-\pi^{erg})\sigma^2_{bull} + \pi^{erg}(1-\pi^{erg})(\mu_{bull} - \mu_{bearl})^2},$$

The Sharpe ratios are computed using a regime-specific riskless interest rate (the U.S. 1-month T-bill yield) computed as the state-specific average of the available data over the sample period 1990:02 – 2009:12. Months in which the smoothed (full-sample) probability of a bear regime exceeds or is equal to 0.5 are classified as bear states; all other months in the sample are classified as bull states.

		Mean Return	Regime-Specific Volatility of Returns	Unconditional (Long-Run) Volatility of Returns	Regime-Specific Sharpe Ratio	Unconditional (Long-Run) Sharpe Ratio
U.S. Local	Bear	0.105	4.886	4.431	-0.005	0.090
	Bull	1.168	3.951		0.193	
Canada Local	Bear	0.461	4.533	4.547	0.041	0.084
	Bull	0.772	4.553		0.099	
U.K. Local	Bear	0.374	4.690	4.327	0.022	0.107
	Bull	0.906	3.986		0.147	
Japan Local	Bear	-0.265	5.713	5.802	-0.094	-0.062
	Bull	0.022	5.872		-0.051	
Asia ex-Japan	Bear	0.577	5.764	5.570	0.053	0.056
	Bull	0.636	5.404		0.058	
Europe ex-UK	Bear	0.201	5.974	5.322	-0.012	0.079
	Bull	0.911	4.690		0.126	

Table 9

Two-State Markov Switching Estimates: Sector Stock Return Correlations

The tables reports the MLE/EM estimates from a two-state Markov switching model. In the table, boldfaced coefficients are statistically significant with a p-value of 0.05 or lower.

	U.S. Local	Canada Local	U.K. Local	Japan Local	Asia ex-Japan Local	Europe ex-UK
U.S. Local		**0.748**	**0.674**	**0.386**	**0.602**	**0.661**
Canada Local	**0.823**		**0.583**	**0.407**	**0.626**	**0.648**
U.K. Local	**0.875**	**0.744**		**0.409**	**0.612**	**0.742**
Japan Local	**0.584**	**0.661**	**0.571**		**0.408**	**0.501**
Asia ex-Japan Local	**0.821**	**0.828**	**0.774**	**0.682**		**0.590**
Europe ex-UK	**0.906**	**0.769**	**0.917**	**0.606**	**0.831**	

Table 10

Two-State Markov Switching Estimates: Sector Compensation Growth Estimates and MSCI Stock Index Returns

The table reports the MLE/EM estimates from a two-state Markov switching model. The HQ criterion is an information criterion that trades-off in-sample fit with model parsimony. In the table, the regime-specific means and standard deviations are boldfaced when they turned out to be statistically significant on the basis of a likelihood ratio test of the equality restriction in estimation. When both means and variances are statistically different across regimes and this can be only detected using a joint test, both mean and variance coefficients have been boldfaced.

Compensation Growth		Wage Mean	Wage St. dev.	Contemporaneous Correlation with MSCI International Stock Index Returns					
				U.S. Local	Canada Local	U.K. Local	Japan Local	Asia ex-Japan Local	Europe ex-UK
Non-Durables	Bear	**0.251**	0.461	-0.049	0.005	-0.165**	-0.086	-0.127**	-0.094*
	Bull	**0.231**	0.438	0.069	-0.427***	0.157***	-0.068	0.013	-0.178***
Durables	Bear	**0.217**	2.286	-0.061	-0.114*	-0.044	-0.076	-0.107*	-0.128**
	Bull	0.231	1.089	-0.060	-0.106*	-0.013	0.037	0.140**	-0.066
Manufacturing	Bear	**0.242**	0.408	-0.042	0.088*	-0.035	0.015	0.012	-0.034
	Bull	**0.199**	0.443	0.078	-0.439***	0.015	-0.253***	-0.041	-0.432***
Energy	Bear	**0.248**	0.843	0.017	-0.061	-0.023	-0.138**	-0.029	0.021
	Bull	**0.205**	0.991	0.091	0.174**	0.152**	0.263**	0.251***	0.130**
Chemicals	Bear	**0.271**	0.559	-0.128**	-0.126*	-0.168**	-0.077	-0.109*	-0.119*
	Bull	0.115	0.684	0.006	-0.153**	-0.057	0.130**	-0.058	0.047
Business Eqpm.	Bear	**0.349**	0.517	-0.209***	-0.217**	-0.259***	-0.118**	-0.112**	-0.209***
	Bull	**0.322**	0.792	0.063	-0.031	0.056	0.040	-0.036	0.063
Telecommunic.	Bear	**0.345**	0.613	-0.089*	-0.037	-0.025	-0.017	-0.013	-0.124*
	Bull	**0.229**	0.673	-0.023	-0.081	-0.011	-0.043	-0.079	-0.013
Utilities	Bear	**0.266**	0.691	-0.114*	-0.129*	-0.243**	-0.135**	-0.163**	-0.192**
	Bull	**0.223**	0.678	0.003	-0.101*	0.113*	0.125**	-0.138**	0.070
Shops & Retail	Bear	**0.217**	0.573	-0.320***	-0.210**	-0.362***	-0.258***	-0.267***	-0.266***
	Bull	**0.253**	0.688	0.061	-0.053	-0.034	0.041	-0.080	0.050
Health	Bear	**0.332**	0.332	-0.054	-0.092	-0.123*	-0.026	-0.022	-0.073
	Bull	**0.261**	0.241	0.143*	-0.074	0.123*	-0.276***	-0.044	-0.126**
Money & Finance	Bear	**0.342**	0.590	-0.105*	-0.112*	-0.129*	-0.045	-0.102*	-0.127**
	Bull	**0.289**	0.613	0.001	-0.080	0.014	-0.010	0.092*	0.047

Table 11

Realized, Recursive Out-of-Sample Sharpe Ratios of Constrained Portfolios Under Alternative Background Risk Models

The table reports realized, recursive, Sharpe ratios for mean-variance optimizing portfolios across 7 MSCI international portfolios as a function of the background risk model and the econometric model. Two alternative models are considered: Gaussian IID and a two-state Markov switching model. The calculations are performed with reference to the period Jan. 2002 – Dec. 2009, assuming three alternative risk aversion levels and three horizons. The column "No" refers to the case in which no background risk is taken into account or, equivalently, when the mean-variance portfolio optimizer is not to be employed. Boldfaced Sharpe ratios are the best within a given background risk framework (i.e., for a selected OPF).

Risk Aversion	No	Avg.	NoDur	Durbl	Manuf	Enrgy	Chems	BusEq	Telcm	Utils	Shops	Hlth	Money
	Gaussian IID Model (No Predictability)												
	Short Investment Horizon (1 month)												
High	0.086	0.079	**0.086**	0.086	0.081	0.098	**0.094**	**0.095**	**0.082**	**0.094**	0.098	0.084	**0.092**
Medium	0.086	0.099	**0.091**	0.121	0.075	**0.152**	**0.119**	**0.133**	0.078	**0.155**	**0.127**	0.080	**0.122**
Low	0.086	0.126	**0.104**	0.148	**0.073**	0.198	0.140	0.170	0.107	0.253	0.157	**0.081**	0.158
	Intermediate Investment Horizon (1 year)												
High	0.149	0.157	0.148	0.150	0.140	0.170	**0.157**	0.161	**0.146**	0.161	0.165	**0.147**	**0.158**
Medium	0.149	0.177	0.153	0.183	0.129	0.229	0.184	0.199	0.149	0.218	0.203	0.144	0.189
Low	0.149	0.204	**0.166**	0.205	0.129	0.274	0.208	0.233	0.173	0.288	0.223	0.149	0.221
	Long Investment Horizon (5 years)												
High	0.047	0.048	0.047	0.048	0.047	**0.051**	0.048	0.049	0.047	0.049	0.050	0.047	0.049
Medium	0.047	0.053	0.049	0.056	0.047	0.064	0.051	0.057	0.048	0.062	0.058	0.047	0.055
Low	0.047	0.059	0.052	0.062	0.049	0.076	0.054	0.063	0.054	0.076	0.066	0.050	0.062

Risk Aversion	No	Avg.	NoDur	Durbl	Manuf	Enrgy	Chems	BusEq	Telcm	Utils	Shops	Hlth	Money
	Markov Switching Model (Nonlinear Predictability)												
	Short Investment Horizon (1 month)												
High	**0.218**	**0.214**	0.070	**0.086**	**0.109**	**0.181**	0.070	0.043	0.033	0.088	**0.102**	**0.107**	0.049
Medium	**0.230**	**0.293**	0.090	0.118	**0.080**	0.105	0.102	0.107	**0.126**	0.110	0.115	**0.166**	0.114
Low	**0.104**	**0.319**	0.093	**0.238**	0.055	**0.219**	**0.211**	**0.255**	**0.112**	**0.332**	**0.242**	0.068	**0.236**
	Intermediate Investment Horizon (1 year)												
High	**0.233**	**0.246**	**0.161**	**0.164**	**0.143**	**0.193**	0.143	**0.161**	0.133	**0.204**	**0.197**	0.124	0.150
Medium	**0.252**	**0.303**	**0.177**	**0.208**	**0.144**	**0.260**	**0.216**	**0.244**	**0.231**	**0.260**	**0.233**	**0.159**	**0.224**
Low	**0.226**	**0.302**	0.133	**0.223**	**0.175**	**0.344**	**0.334**	**0.332**	**0.278**	**0.344**	**0.317**	**0.173**	**0.328**
	Long Investment Horizon (5 years)												
High	**0.219**	**0.084**	**0.054**	**0.104**	**0.049**	0.068	**0.051**	**0.062**	**0.057**	**0.078**	**0.067**	**0.052**	**0.057**
Medium	**0.084**	**0.087**	**0.057**	**0.071**	**0.053**	**0.087**	**0.058**	**0.282**	**0.060**	**0.090**	**0.080**	**0.055**	**0.074**
Low	**0.065**	**0.082**	**0.069**	**0.071**	**0.066**	**0.089**	**0.078**	**0.087**	**0.077**	**0.090**	**0.088**	**0.065**	**0.087**

Table 12

Out-of-Sample Sharpe Ratios Loss from Background Risk Exposure: Constrained Portfolios

The table reports realized, recursive, out-of-sample declines in Sharpe ratios vs. the case of no background risk (i.e., when the investor is not employed) for mean-variance optimizing portfolios across 7 MSCI international portfolios as a function of the background risk model and the econometric model used to capture any predictability in the dynamic relationship between employee total compensation and stock returns. Two alternative models are considered: Gaussian IID and a two-state Markov switching model. The calculations are performed with reference to the period Jan. 2002 – Dec. 2009, assuming three alternative risk aversion levels and three horizons. All Sharpe ratios are reported in annualized levels. Boldfaced Sharpe ratios indicate that the Sharpe ratio loss is negative, i.e., that an investor may gain in realized terms in spite of her taking into account of background risk.

Risk Aversion	NoDur	Durbl	Manuf	Enrgy	Chems	BusEq	Telcm	Utils	Shops	Hlth	Money
	Gaussian IID Model (No Predictability)										
	Short Investment Horizon (1 month)										
High	0.000	0.000	0.005	**-0.012**	**-0.007**	**-0.008**	0.004	**-0.008**	**-0.012**	0.002	**-0.006**
Medium	**-0.005**	**-0.034**	0.011	**-0.065**	**-0.033**	**-0.046**	0.008	**-0.069**	**-0.041**	0.006	**-0.036**
Low	**-0.018**	**-0.062**	0.013	**-0.112**	**-0.054**	**-0.083**	**-0.020**	**-0.166**	-0.071	0.006	**-0.071**
	Intermediate Investment Horizon (1 year)										
High	0.002	**-0.001**	0.009	**-0.021**	**-0.008**	**-0.011**	0.003	**-0.012**	**-0.016**	0.002	**-0.009**
Medium	**-0.003**	**-0.034**	0.020	**-0.080**	**-0.035**	**-0.050**	0.001	**-0.069**	**-0.054**	0.006	**-0.040**
Low	**-0.017**	**-0.056**	0.020	**-0.125**	**-0.059**	**-0.084**	**-0.024**	**-0.139**	**-0.074**	0.000	**-0.072**
	Long Investment Horizon (5 years)										
High	0.000	**-0.001**	0.001	**-0.003**	**-0.001**	**-0.002**	0.001	**-0.002**	**-0.002**	0.000	**-0.001**
Medium	**-0.001**	**-0.009**	0.001	**-0.017**	**-0.003**	**-0.009**	**-0.001**	**-0.014**	**-0.011**	0.000	**-0.008**
Low	**-0.005**	**-0.015**	**-0.002**	**-0.028**	**-0.007**	**-0.016**	**-0.007**	**-0.029**	**-0.019**	**-0.002**	**-0.014**

Risk Aversion	NoDur	Durbl	Manuf	Enrgy	Chems	BusEq	Telcm	Utils	Shops	Hlth	Money
	Markov Switching Model (Nonlinear Predictability)										
	Short Investment Horizon (1 month)										
High	0.148	0.132	0.109	0.037	0.148	0.175	0.185	0.130	0.116	0.111	0.169
Medium	0.139	0.111	0.150	0.125	0.127	0.123	0.104	0.120	0.115	0.063	0.116
Low	0.010	**-0.135**	0.049	**-0.115**	**-0.108**	**-0.151**	**-0.008**	**-0.229**	**-0.138**	0.036	**-0.133**
	Intermediate Investment Horizon (1 year)										
High	0.072	0.069	0.090	0.040	0.090	0.072	0.100	0.029	0.036	0.109	0.083
Medium	0.075	0.044	0.108	**-0.008**	0.036	0.008	0.021	**-0.008**	0.018	0.092	0.028
Low	0.093	0.003	0.051	**-0.118**	**-0.108**	**-0.107**	**-0.052**	**-0.118**	**-0.091**	0.053	**-0.102**
	Long Investment Horizon (5 years)										
High	0.166	0.115	0.171	0.152	0.168	0.157	0.162	0.142	0.153	0.167	0.163
Medium	0.027	0.013	0.030	**-0.003**	0.026	**-0.199**	0.023	**-0.006**	0.003	0.028	0.010
Low	**-0.004**	**-0.006**	**-0.001**	**-0.024**	**-0.013**	**-0.022**	**-0.012**	**-0.026**	**-0.023**	**-0.001**	**-0.022**

Table 13

Two-State Markov Switching Estimates: U.K. Sectoral Stock Return Estimates

The table reports the MLE/EM estimates from a two-state Markov switching model. The unconditional volatility is computed using the ergodic state probabilities implied by the model and according to the formula:

$$\sigma^{erg} = \sqrt{\pi^{erg}\sigma_{bear}^{2} + (1-\pi^{erg})\sigma_{bull}^{2} + \pi^{erg}(1-\pi^{erg})(\mu_{bull} - \mu_{bearl})^{2}} \ ,$$

The Sharpe ratios are computed using a regime-specific riskless interest rate (the U.S. 1-month T-bill yield) computed as the state-specific average of the available data over the sample period 2000:01 – 2010:12. Months in which the smoothed (full-sample) probability of a bear regime exceeds or is equal to 0.5 are classified as bear states; all other months in the sample are classified as bull states.

		Mean Return	**Regime-Specific Volatility of Returns**	**Unconditional (Long-Run) Volatility of Returns**	**Regime-Specific Sharpe Ratio**	**Unconditional (Long-Run) Sharpe Ratio**
Industrials	Bear	-0.250	11.079	7.399	-0.043	0.104
	Bull	1.698	4.782		0.268	
Agriculture, Forestry and Fishing	Bear	0.526	5.361	4.162	0.055	0.190
	Bull	1.374	3.456		0.277	
Mining and Quarrying	Bear	1.229	8.256	6.164	0.121	0.210
	Bull	1.785	4.927		0.278	
Electricity, Gas and Water Supply	Bear	-1.186	8.204	6.499	-0.172	0.066
	Bull	1.618	5.337		0.225	
Constructions	Bear	0.622	6.243	4.754	0.063	0.045
	Bull	0.485	3.900		0.017	
Retail Trade and Repairs	Bear	0.053	7.790	5.889	-0.023	0.022
	Bull	0.617	4.780		0.042	
Financial Intermediation	Bear	-1.273	7.101	6.587	-0.212	0.029
	Bull	1.312	6.175		0.145	

Table 14

Two-State Markov Switching Estimates: U.K. Sectoral Stock Return Correlations

The tables reports the MLE/EM estimates from a two-state Markov switching model. In the table, boldfaced coefficients are statistically significant with a p-value of 0.05 or lower.

	Industrials	Agriculture, Forestry and Fishing	Mining and Quarrying	Electricity, Gas and Water Supply	Constructions	Retail Trade and Repairs	Financial Intermediation
Industrials		**0.449**	**0.644**	**0.762**	**0.721**	**0.777**	**0.646**
Agriculture, Forestry and Fishing	**0.355**		**0.563**	**0.534**	**0.667**	**0.398**	**0.456**
Mining and Quarrying	**0.288**	**0.665**		**0.518**	**0.686**	**0.656**	**0.640**
Electricity, Gas and Water Supply	**0.595**	**0.471**	**0.426**		**0.649**	**0.860**	**0.543**
Constructions	**0.331**	**0.615**	**0.551**	**0.554**		**0.666**	**0.480**
Retail Trade and Repairs	**0.445**	**0.448**	**0.228**	**0.525**	**0.584**		**0.607**
Financial Intermediation	**0.216**	**0.235**	0.143	0.188	**0.358**	0.298	

Table 15

Two-State Markov Switching Estimates: Sector Compensation Growth Estimates and U.K. Sectoral Stock Returns

The table reports the MLE/EM estimates from a two-state Markov switching model. The HQ criterion is an information criterion that trades-off in-sample fit with model parsimony. In the table, the regime-specific means and standard deviations are boldfaced when they turned out to be statistically significant on the basis of a likelihood ratio test of the equality restriction in estimation. When both means and variances are statistically different across regimes and this can be only detected using a joint test, both mean and variance coefficients have been boldfaced.

Compensation Growth		Wage Mean	Wage St. dev.	Contemporaneous Correlation with U.K. Sectoral Stock Returns							State persistence	Avg. Duration	Ergodic Prob.	LR Linearity Test	HQ criterion
				Industrials	Agriculture, Forestry and Fishing	Mining and Quarrying	Electricity, Gas and Water Supply	Constructions	Retail Trade and Repairs	Financial Intermediation					
Industrials	Bear	-0.430	2.313	-0.203**	-0.122*	-0.127*	-0.177**	-0.219**	-0.315***	-0.077	0.537	2.16	0.520	99.79	47.809
	Bull	**1.519**	4.743	-0.116*	-0.126*	0.003	0.079	0.044	0.219**	-0.275**	0.498	1.99	0.480	(0.000)	Linear: 47.444
Agriculture, Forestry and Fishing	Bear	0.226	3.409	-0.279**	-0.010	-0.050	-0.221**	-0.175**	-0.173**	-0.198**	0.517	2.07	0.436	91.94	47.745
	Bull	0.665	3.785	0.076	0.260***	0.028	0.288**	0.298**	0.333***	0.013	0.626	2.67	0.564	(0.000)	Linear: 47.315
Mining and Quarrying	Bear	-0.856	5.380	-0.158**	-0.084	-0.064	-0.024	-0.261***	-0.145**	-0.013	0.783	4.61	0.789	132.54	49.292
	Bull	**9.020**	14.32	-0.165**	-0.316***	-0.214**	-0.162**	-0.339***	-0.198**	-0.535***	0.192	1.24	0.211	(0.000)	Linear: 49.150
Electricity, Gas and Water Supply	Bear	0.533	3.067	-0.138*	0.024	-0.022	-0.084	-0.040	-0.234**	-0.435***	0.514	2.06	0.395	94.349	47.030
	Bull	0.418	3.194	-0.129*	0.114*	-0.013	-0.000	0.043	0.254**	-0.058	0.683	3.16	0.605	(0.000)	Linear: 47.440
Constructions	Bear	-0.114	1.642	-0.163*	-0.185**	-0.144*	0.002	-0.100*	-0.094*	0.012	0.656	2.91	0.636	107.40	46.258
	Bull	**1.248**	2.461	0.387***	-0.176**	0.097	0.098*	-0.054	0.137*	-0.181**	0.399	1.66	0.364	(0.000)	Linear: 46.562
Retail Trade and Repairs	Bear	**0.421**	2.176	0.211**	0.247**	0.218**	0.264**	0.188**	0.157*	0.024	0.828	5.80	0.645	105.17	46.538
	Bull	0.424	3.012	-0.278**	0.429***	0.111*	0.157*	0.336**	0.193**	-0.043	0.687	3.19	0.355	(0.000)	Linear: 46.859
Financial Intermediation	Bear	**0.197**	1.022	0.056	0.085	0.051	-0.023	-0.147*	-0.036	0.051	0.716	3.52	0.733	90.31	44.815
	Bull	**0.852**	0.887	0.135*	0.020	0.262**	0.252**	0.107*	0.094	-0.115*	0.220	1.28	0.267	(0.000)	Linear: 45.259

Table 16

Realized Out-of-Sample Sharpe Ratios of Constrained Portfolios Under Alternative Background Risk Models: United Kingdom Sectoral Diversification

The table reports realized, recursive, Sharpe ratios for mean-variance optimizing portfolios across 7 U.K. sectoral portfolios as a function of the background risk and the econometric model. Two alternative models are considered: Gaussian IID and a two-state Markov switching model. The calculations are performed with reference to the period Jan. 2007 – Dec. 2010, assuming three alternative risk aversion levels and two horizons. The column "No" refers to the case in which no background risk is taken into account or, equivalently, when the mean-variance portfolio optimizer is not to be employed. Boldfaced Sharpe ratios are the best within a given background risk framework (i.e., for a selected OPF).

Risk Aversion	No	Avg.	Industrials	Agriculture, Forestry and Fishing	Mining and Quarrying	Electricity, Gas and Water Supply	Constructions	Retail Trade and Repairs	Financials	No	Avg.	Industrials	Agriculture, Forestry and Fishing	Mining and Quarrying	Electricity, Gas and Water Supply	Constructions	Retail Trade and Repairs	Financials
	Gaussian IID Model (No Predictability)									Markov Switching Model (Nonlinear Predictability)								
	Short Investment Horizon (1 month)																	
High	**0.163**	0.218	**0.264**	**0.286**	**0.493**	0.179	0.273	0.074	0.133	0.005	**0.287**	-0.093	0.269	0.383	**0.407**	**0.368**	**0.279**	**0.520**
Medium	0.163	0.218	0.291	0.612	**0.457**	0.425	0.272	0.200	-0.048	**0.343**	**0.326**	**0.660**	**0.994**	0.379	**0.460**	**0.560**	**0.151**	**0.321**
Low	0.163	0.218	0.420	0.634	**0.346**	**0.592**	0.318	0.191	-0.348	**0.440**	**0.726**	**0.518**	**0.956**	0.326	0.275	**0.355**	**0.194**	**0.199**
	Intermediate Investment Horizon (1 year)																	
High	0.532	0.536	**0.595**	0.569	0.570	0.501	0.636	0.516	**0.484**	**0.580**	**0.575**	0.504	**0.722**	**0.632**	**0.665**	**0.759**	**0.615**	0.363
Medium	0.532	0.536	**0.566**	0.594	0.481	**0.495**	0.540	0.334	0.347	**0.586**	**0.597**	0.514	**0.642**	**0.646**	0.474	**0.708**	**0.438**	**0.367**
Low	0.532	0.536	0.481	**0.680**	0.636	**0.676**	0.562	**0.449**	0.137	**0.601**	**0.596**	**0.556**	0.636	**0.640**	0.463	**0.631**	0.376	**0.350**

Table 17

Out-of-Sample Sharpe Ratios Loss from Background Risk Exposure: Constrained, United Kingdom Sectoral Portfolios

The table reports realized, recursive, out-of-sample declines in Sharpe ratios vs. the case of no background risk (i.e., when the investor is not employed) for mean-variance optimizing portfolios across 7 U.K. sectoral portfolios as a function of the background risk model and the econometric model used to capture any predictability in the dynamic relationship between employee total compensation and stock returns. Two alternative models are considered: Gaussian IID and a two-state Markov switching model. The calculations are performed with reference to the period Jan. 2007 – Dec. 2010, assuming three alternative risk aversion levels and two horizons. All Sharpe ratios are reported in annualized levels. Boldfaced Sharpe ratios indicate that the Sharpe ratio loss is negative, i.e., that an investor may gain in realized terms in spite of her taking into account of background risk.

Risk Aversion	Industrials	Agriculture, Forestry and Fishing	Mining and Quarrying	Electricity, Gas and Water Supply	Constructions	Retail Trade and Repairs	Financials	Industrials	Agriculture, Forestry and Fishing	Mining and Quarrying	Electricity, Gas and Water Supply	Constructions	Retail Trade and Repairs	Financials
	Gaussian IID Model (No Predictability)							Markov Switching Model (Nonlinear Predictability)						
	Short Investment Horizon (1 month)													
High	**-0.102**	**-0.124**	**-0.331**	**-0.017**	**-0.111**	0.088	0.029	0.099	**-0.264**	**-0.378**	**-0.402**	**-0.363**	**-0.274**	**-0.515**
Medium	**-0.129**	**-0.450**	**-0.294**	**-0.263**	**-0.109**	**-0.038**	0.210	**-0.317**	**-0.651**	**-0.036**	**-0.116**	**-0.217**	0.192	0.022
Low	**-0.257**	**-0.471**	**-0.183**	**-0.430**	**-0.156**	**-0.028**	0.510	**-0.078**	**-0.516**	0.114	0.165	0.085	0.246	0.241
	Intermediate Investment Horizon (1 year)													
High	**-0.063**	**-0.037**	**-0.037**	0.032	**-0.104**	0.017	0.048	0.075	**-0.142**	**-0.053**	**-0.085**	**-0.180**	**-0.036**	0.217
Medium	**-0.034**	**-0.062**	0.051	0.038	**-0.007**	0.198	0.185	0.071	**-0.056**	**-0.061**	0.112	**-0.122**	0.148	0.219
Low	0.051	**-0.148**	**-0.104**	**-0.144**	**-0.030**	0.083	0.395	0.045	**-0.035**	**-0.039**	0.138	**-0.030**	0.226	0.252

Table 18

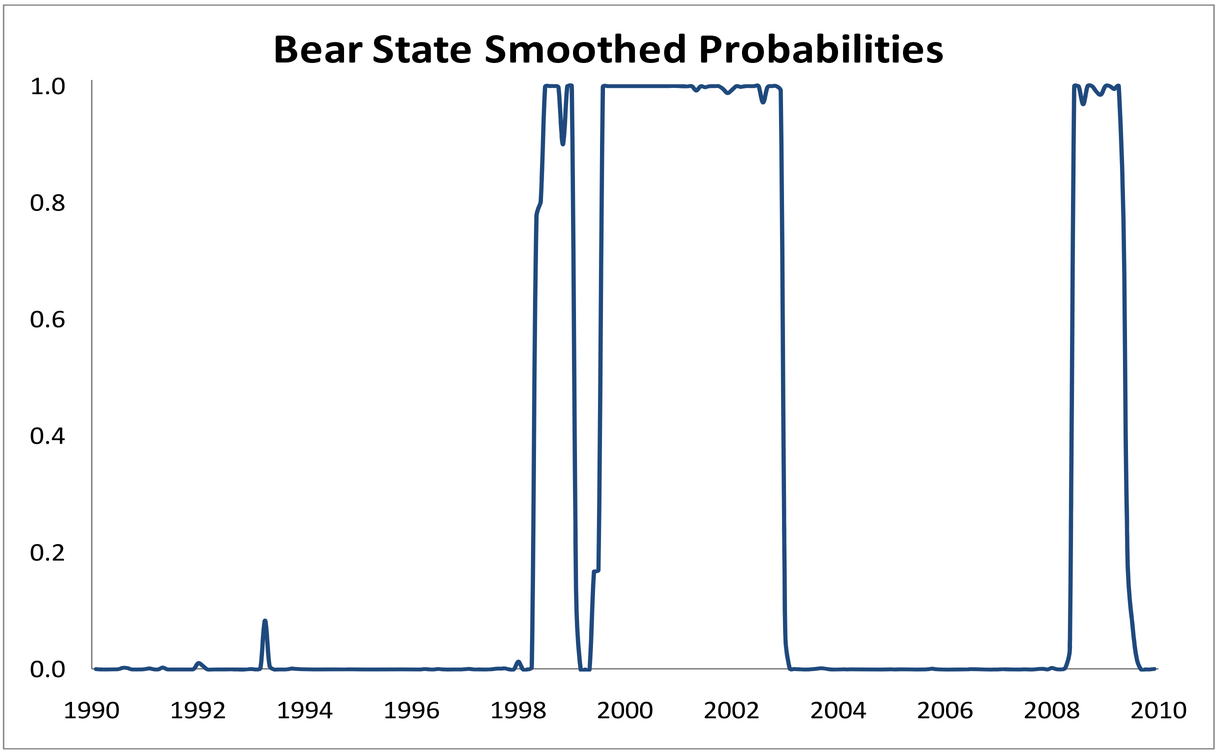
Realized Out-of-Sample Sharpe Ratios of Constrained Portfolios Under Alternative Background Risk Models: United Kingdom International Diversification

The table reports realized, recursive, Sharpe ratios for mean-variance optimizing portfolios across 5 MSCI international portfolios as a function of the background risk and the econometric model. Two alternative models are considered: Gaussian IID and a two-state Markov switching model. The calculations are performed with reference to the period Jan. 2007 – Dec. 2010, assuming three alternative risk aversion levels and two horizons. The column "No" refers to the case in which no background risk is taken into account or, equivalently, when the mean-variance portfolio optimizer is not to be employed. Boldfaced Sharpe ratios are the best within a given background risk framework (i.e., for a selected OPF).

	No	Avg.	Industrials	Agriculture, Forestry and Fishing	Mining and Quarrying	Electricity, Gas and Water Supply	Constructions	Retail Trade and Repairs	Financials	No	Avg.	Industrials	Agriculture, Forestry and Fishing	Mining and Quarrying	Electricity, Gas and Water Supply	Constructions	Retail Trade and Repairs	Financials
Risk Aversion	Gaussian IID Model (No Predictability)									Markov Switching Model (Nonlinear Predictability)								
	Short Investment Horizon (1 month)																	
High	**-0.008**	**-0.071**	-0.111	**-0.133**	-0.061	-0.057	**-0.062**	**-0.073**	-0.014	-0.106	-0.146	**-0.029**	-0.321	**0.190**	**-0.034**	-0.280	-0.304	**0.010**
Medium	-0.008	**-0.071**	-0.246	-0.181	-0.363	-0.142	-0.163	-0.116	-0.021	**0.127**	-0.228	**-0.043**	**-0.151**	**-0.044**	**0.028**	**-0.033**	**-0.040**	**0.221**
Low	-0.008	**-0.071**	-0.253	-0.202	-0.351	-0.152	-0.205	-0.163	**-0.069**	**0.137**	-0.195	**-0.168**	**-0.133**	**-0.207**	**-0.083**	**-0.141**	**0.057**	-0.138
	Intermediate Investment Horizon (1 year)																	
High	0.064	0.015	**-0.027**	-0.032	-0.014	0.009	**0.022**	**0.103**	**0.074**	**0.155**	**0.123**	-0.075	**-0.027**	**0.096**	**0.045**	0.014	-0.140	-0.003
Medium	0.064	**0.015**	-0.160	-0.084	-0.323	-0.099	-0.061	-0.036	**0.128**	**0.235**	-0.042	**-0.053**	**0.025**	**-0.277**	**-0.020**	**-0.022**	**-0.017**	0.111
Low	0.064	**0.015**	-0.179	-0.116	-0.304	-0.151	-0.115	-0.064	**0.110**	**0.233**	-0.099	**-0.067**	**0.011**	**-0.227**	**-0.041**	**-0.063**	**0.055**	-0.047

Figure 1

Smoothed State Probabilities from a Two-State Markov Switching Model: U.S. Sectoral Portfolio Returns



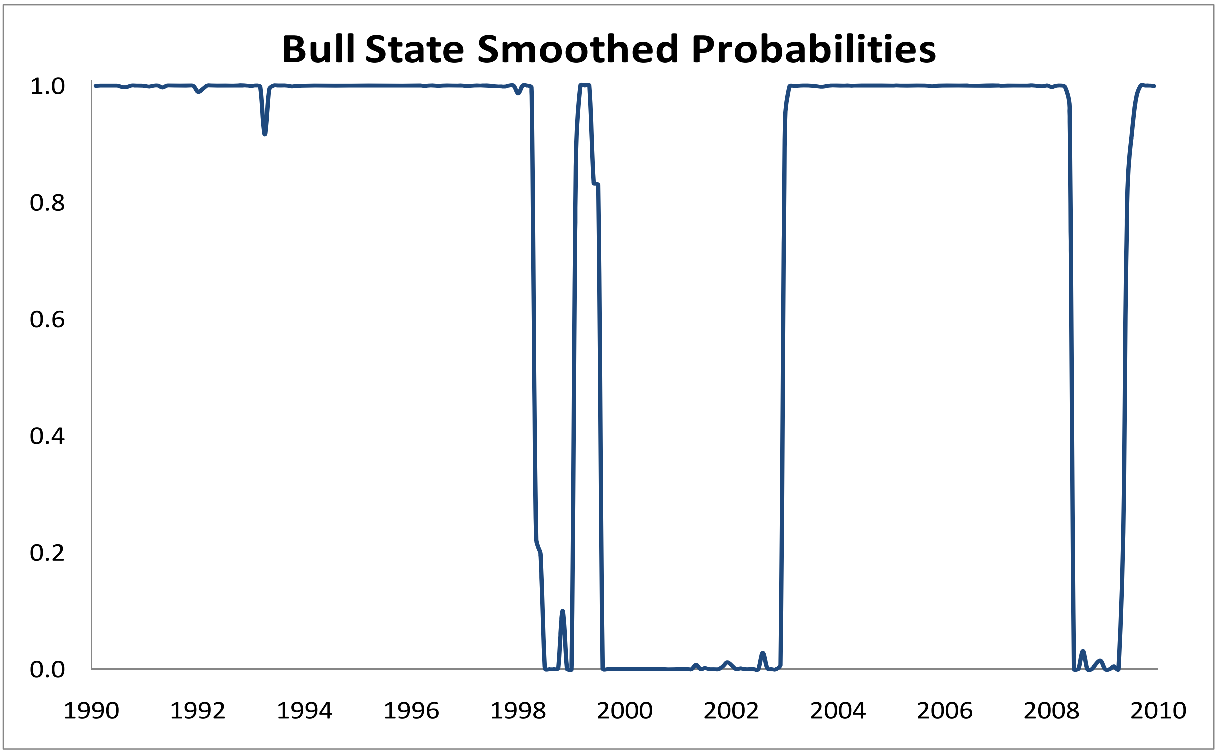


Figure 2

Average Sectoral Portfolio Composition Across Different Background Risk Models Under Mild Risk Aversion Preferences and 1-month Mean-Variance Objective: 2002-2009

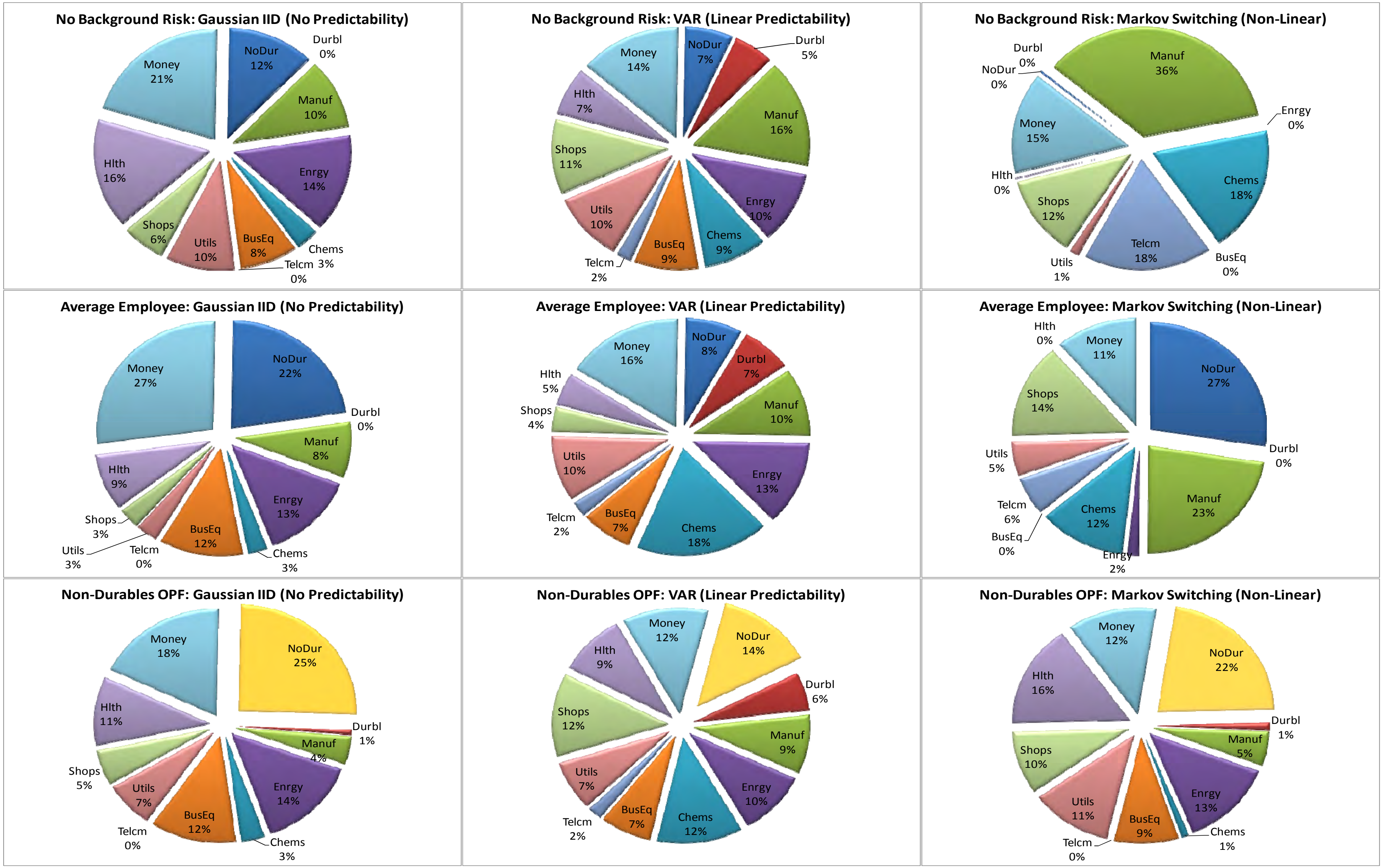
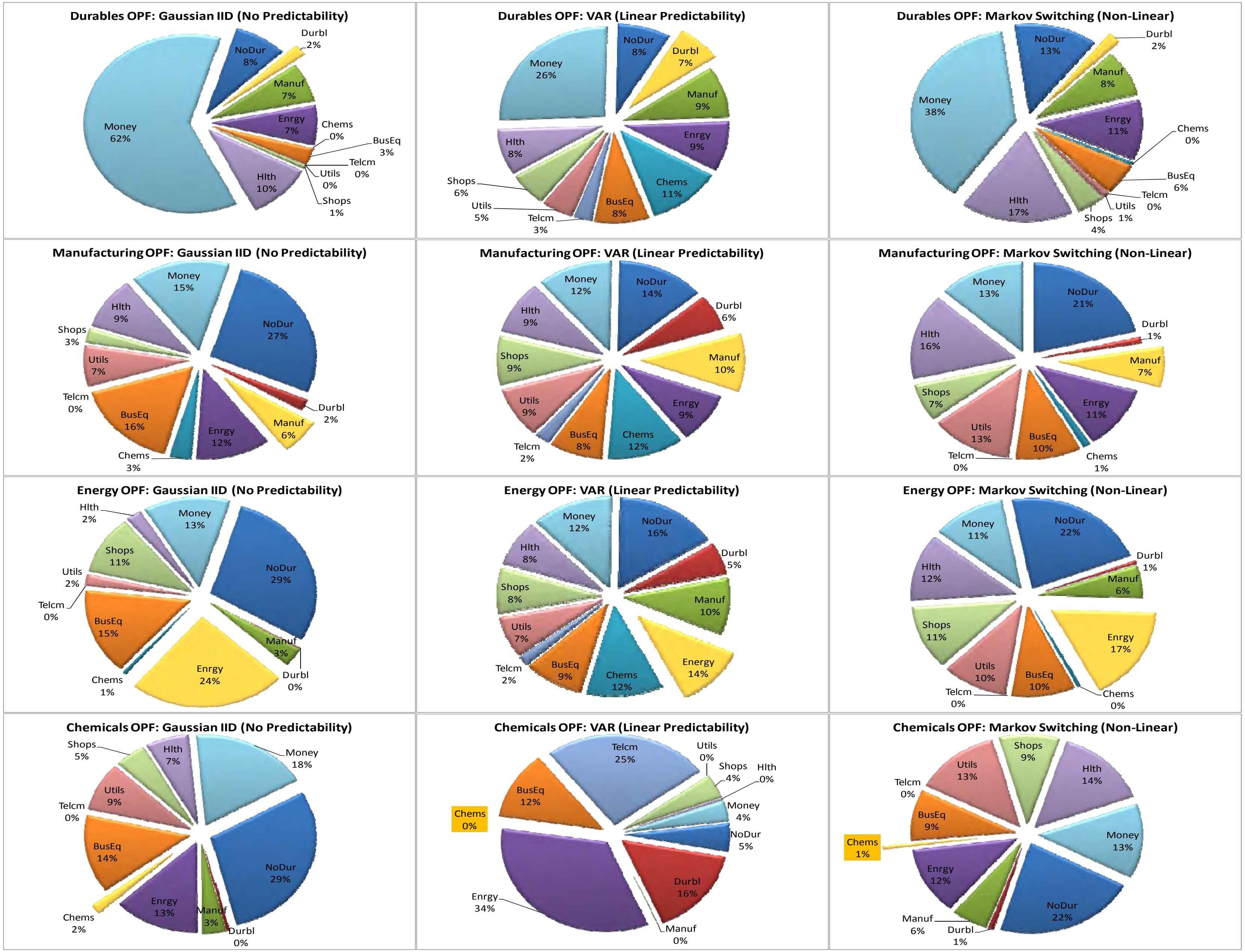


Figure 2 (continued)



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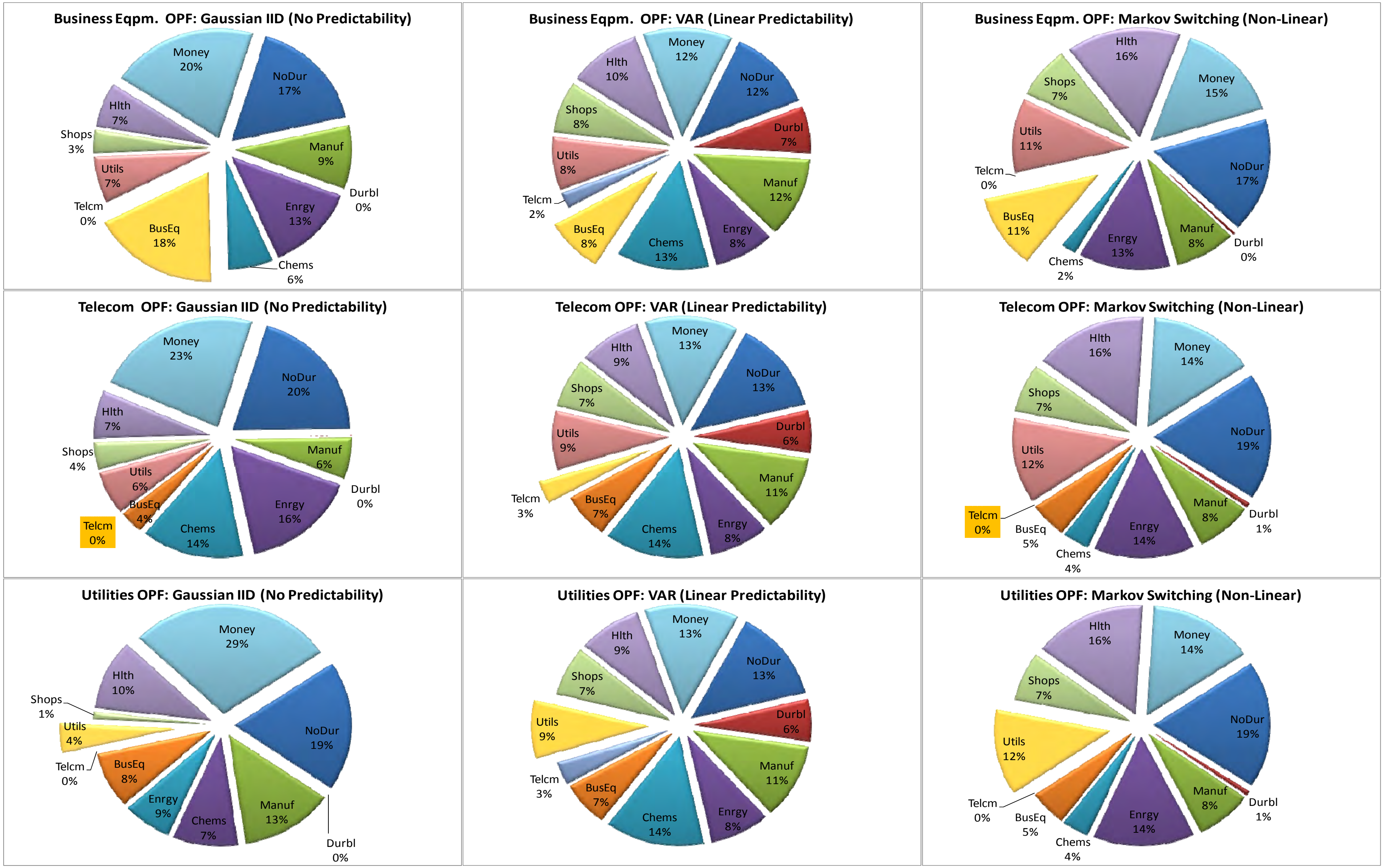

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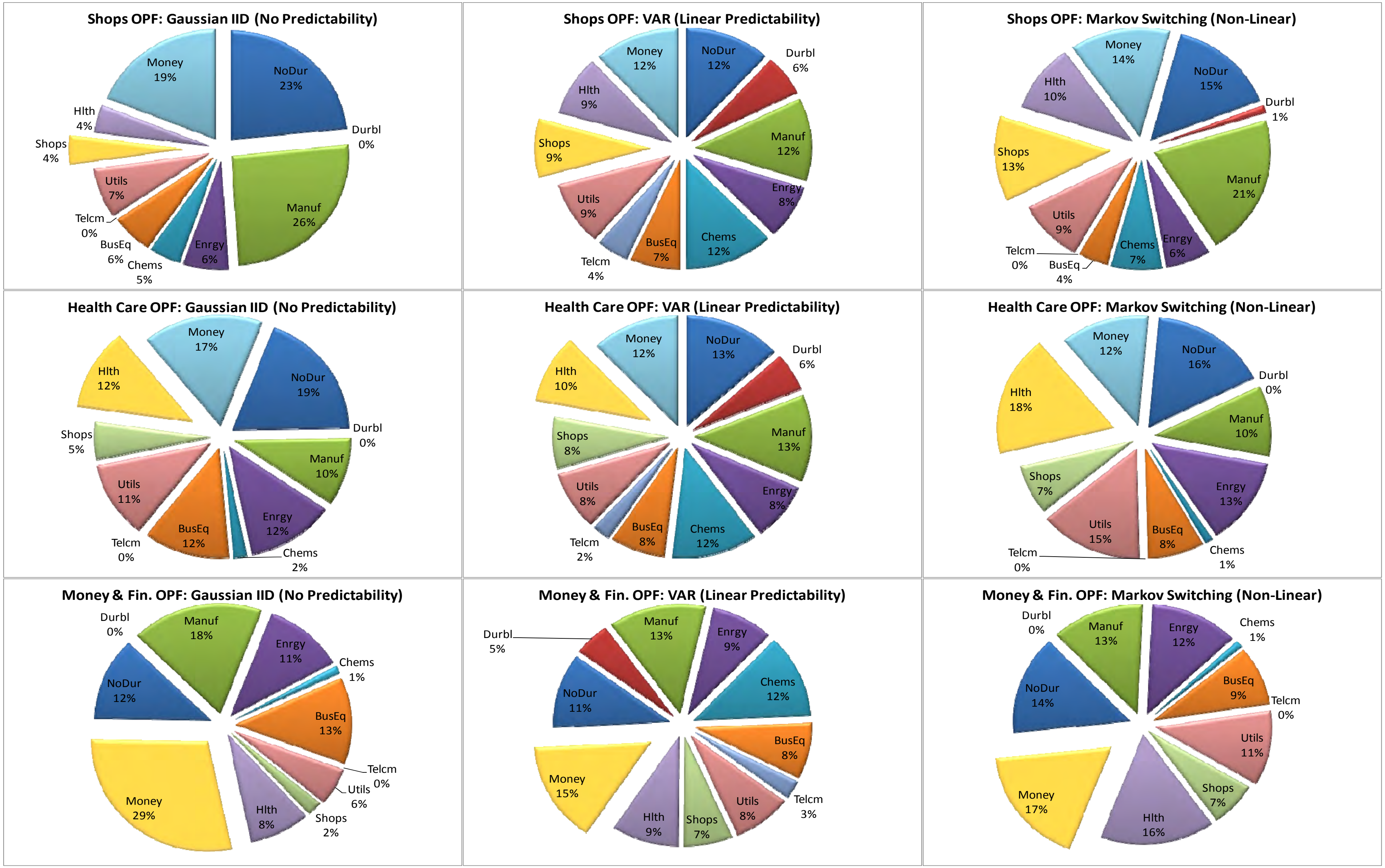
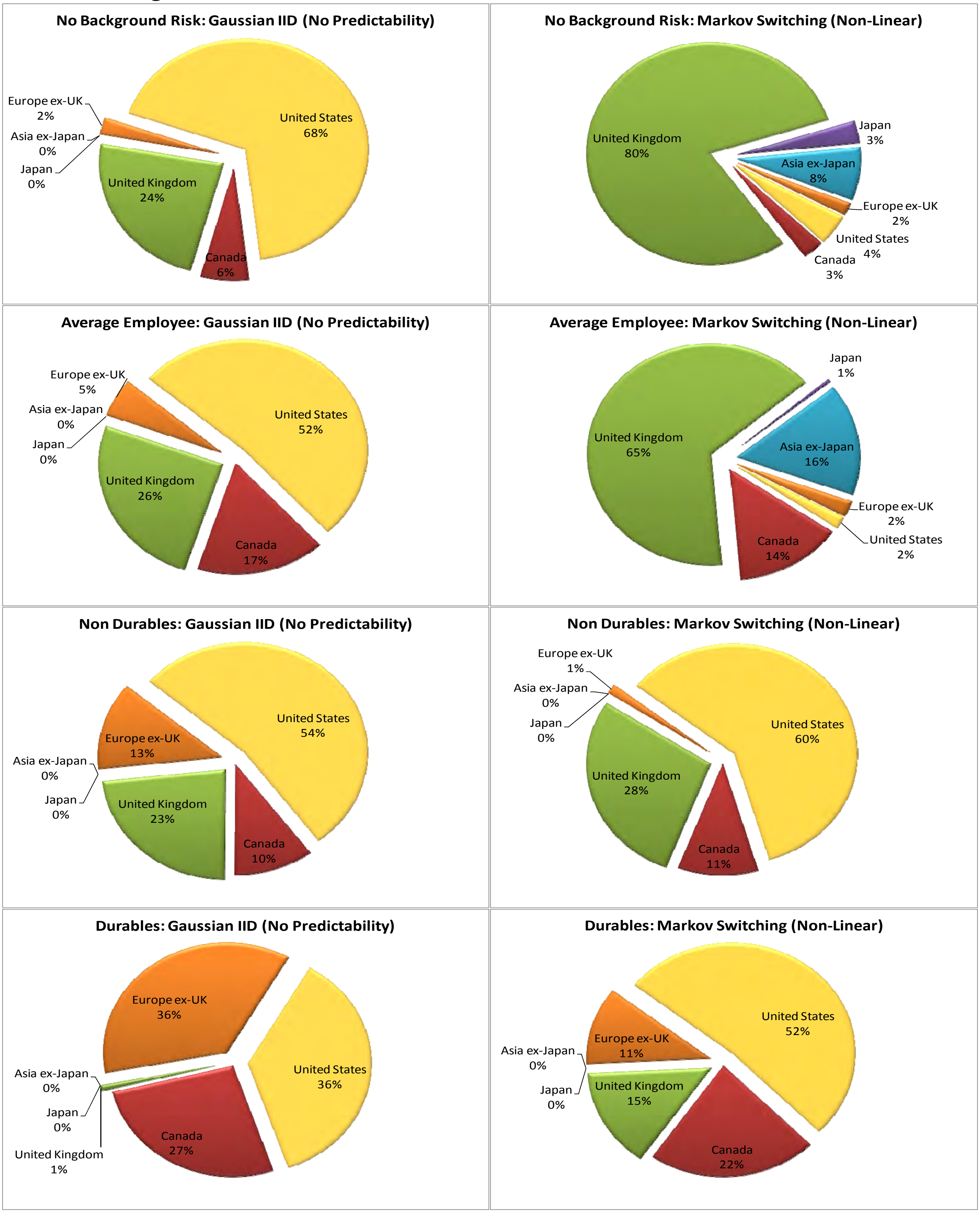


Figure 3

Average International Portfolio Composition Across Different Background Risk Models Under Mild Risk Aversion Preferences: 2002-2009



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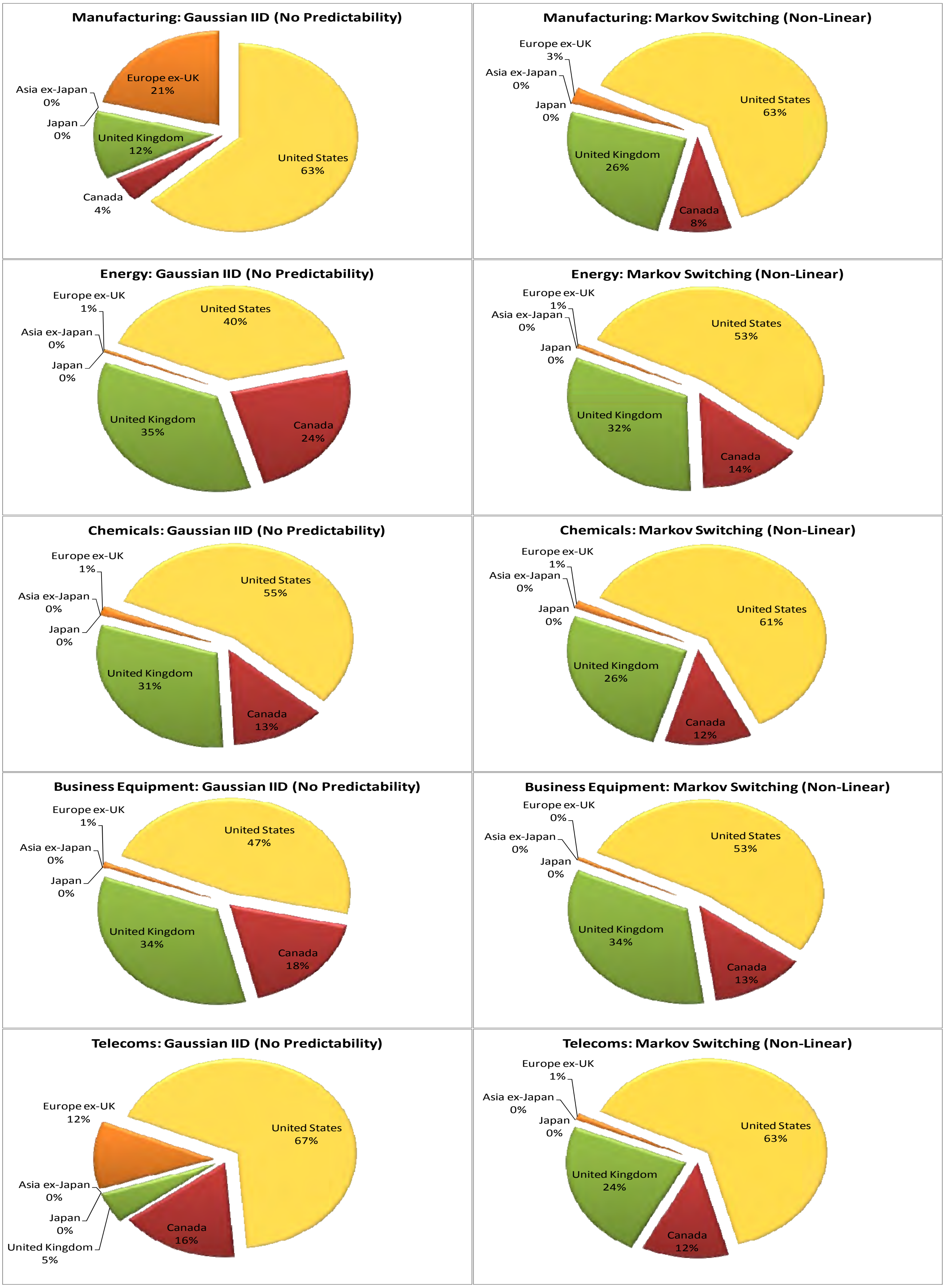

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