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Optimal Privatization Portfolios in the Presence of Arbitrary Risk Aversion

George Christodoulakis[1], Abdulkadir Mohamed[2], Nikolas Topaloglou[3]

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Abstract

We consider the global portfolio of privatized state assets from 1985 to 2012 in the non-parametric decision-making context of Stochastic Dominance Efficiency for broad classes of investor preferences. We estimate all possible portfolios in the context of Strategic vs non-Strategic and Cyclical vs non-Cyclical asset allocations that dominate the market benchmark and provide a complete efficiency ranking. The optimal solutions are computed using linear and mixed integer programming formulations. Dominant portfolios tend to overweight non-Cyclical and non-Strategic assets, while rotation may take place across business cycles. Bayesian investment style return attribution analysis, based on Monte Carlo Integration, suggests that Growth drives returns during the first business cycle, rotating to a balanced mix of styles with Size and Debt Leverage during the second business cycle and finally to Size during the last business cycle. Value is found to be the least influential style in all periods.

Keywords: (B) Finance; Portfolio; Privatization; Stochastic Dominance; Investment Style

[1] Corresponding Author: Alliance Manchester Business School, Booth Street West, Manchester M15 6PB, UK, email george.christodoulakis (at) mbs.ac.uk, tel +44 (0) 161 30 66 404. The paper was motivated when George Christodoulakis served as the State Secretary for Asset Privatizations of Greece, 2009-2012.

[2] Cranfield School of Management, College Road, Cranfield MK43 0AL, United Kingdom, abdulkadir.mohamed (at) cranfield.ac.uk, tel +44 (0)1234 751122

[3] DIEES, Athens University of Economics and Business, 76 Patission Ave, 104 34, Athens, Greece, nikolas (at) aueb.gr, tel +30-210-8203386

1. Introduction

Portfolio optimality and performance lie at the centre of asset management, yet model risk continues to play a central role in preventing practical applications of quantitative approaches. We examine for the first time in the literature the robustness of optimality and performance attribution of privatized state asset portfolios, through a new interdisciplinary approach, with applications to a unique global data set. In particular, our work adopts a new decision making framework in the context of Stochastic Dominance Efficiency, allowing non-parametric analysis for broad classes of utility functions, which are optimized through mixed-integer and linear programming, while performance attribution is developed in the context of a robust Bayesian approach through Monte Carlo Integration methods. Moreover, as massive data requirements prevent the application of parametric portfolio optimization to privatized state assets, our choice to apply non-parametric methods is unique in the finance literature, where we have collected the most comprehensive global data set on an asset universe that constitutes a global policy issue since early 1980s.

State assets constitute a major asset universe. The origin of state participation in various sectors of the economy sets its historical roots in the periodic political perceptions for the protection of public interests, the offer of public goods and the substitution of market failures. Shleifer (1998) provides a comprehensive account of state versus private ownership. As such, we observe state ownership primarily in infrastructure assets, networks, utilities, mining, energy, gaming as well as real estate and much less in manufacturing. The process of privatisation emerged in early 1980s and was largely motivated by the presence of inefficient management in state assets in the form of higher running costs and moral hazards, contributing to the exacerbation of government budget deficits. Shleifer and Vishny (1994), and Boycko et al (1996) provide clear conditions under which privatizations are an optimal choice and La Porta et al (2002) and Faccio (2006) provide the associated empirical evidence. The portfolio of state assets naturally incorporates long term interests of the society, thus professionally run privatization transactions constitute complex processes, trading-off political, economic, financial, legal, regulatory and geopolitical dimensions. The presence of state ownership in an asset is long term and signifies political interests on behalf of the society for the protection of public interest. As a result, the two most fundamental classifications of state assets distinguish between Strategic versus non-Strategic and Cyclical versus non-Cyclical assets. The former classification concerns assets which require expertise in their management, thus a privatization process in this case usually focuses on long-term investors originating from the same industry and excludes purely financial investors(see OECD 2010). For example, as a matter of policy, a state has natural remaining interests in assets involving public infrastructure for the provision of public goods, such as airports, ports and networks, and invites specialist non-financial investors (often called Strategic) e.g. for a concession agreement, see for example Czerny et al. (2014). The latter is a fundamental risk classification for asset managers which primarily concerns infrastructure assets, often in the form of companies holding concession agreements, or the financial sector, versus other conventional assets (see J.P.Morgan 2012). The distinction of Cyclical vs non-Cyclical assets reflects the most fundamental value driver from the point of view of a long-term investor, as privatization is by construction a long-term investment commitment. It is indicative that most investment banks and asset managers follow closely the developments in these two broad asset classes, see for example Morningstar (2011), Lebovitz et al (2016).

The literature contributes a plethora of theoretical and empirical papers on privatization. However, to the best of our knowledge, there is no comprehensive study focusing on the optimality properties of global privatization portfolio selection and the respective performance attribution to asset management style properties. Although the privatization of state assets constitutes a major global policy choice over the last three decades and the literature has converged regarding its general positive effects on the economy, the available empirical research focuses primarily on its impact to the efficiency of individual assets. The literature is very limited on the behaviour of privatized assets from a portfolio perspective, thus failing to inform government privatization planning and active asset management, offering a relatively recent and small number of studies. Li et al (2011) provide empirical evidence from China documenting that, the listing of new shares in the market requires a form of compensation from holders of non-tradable shares to holders of tradable shares, the size of which is related to the gain in risk sharing as well as the price impact of new shares in the market. Dewenter and Malatesta (1997) report evidence on the determinants of privatization initial returns, which are shown to be significantly higher in less developed capital markets and for companies in regulated industries. Moreover, Megginson et al (2000) examine the one-, three- and five-year buy-and-hold returns, earned by investors in share issue privatizations for 33 countries from 1981 to 1997, and compare with domestic market portfolio, global market portfolios and S&P 500 returns. Their evidence suggests that privatization investors earn higher returns than those who invest in the local, US or world market portfolios. In a recent study, Borisova and Cowan (2012) examine the investor returns in 1984 transactions which took place from 1984 to 2009 in 123 countries. Their findings suggest that privatization through asset trade sales to domestic, non-privatized investors yields high returns in less developed countries under a civil law system and a left-wing government. Moreover, post bail-out state assets tend to yield higher returns when compared to all other state sell-offs. Finally, a number of papers study the value of a controlling stake in a privatized firm. Dyck and

Zingales (2004) study 393 controlling blocks sales in 39 countries and report an average value of control 14%, ranging from -4% to +65%, where higher values are associated with immature capital markets, concentrated ownership and privately negotiated transactions. Atanasov (2005) presents more extreme evidence from the Bulgarian stock market where, in the absence of legal constraints, majority owners tend to extract more than 85% of firm value as private benefits of control.

In this paper, we consider the perspective of a long-term asset manager making choices in the global universe of exchange-traded privatised state assets within four sequential periods, from the emergence of privatizations in 1985 to 2012. We address two questions. First, what is the set of asset allocation decisions on Strategic vs. non-Strategic and Cyclical vs. non-Cyclical asset classes that first- or second-degree stochastically dominate a benchmark portfolio approximating the market?. Second, if such a finite set of portfolios exists, is it possible to attribute their performance to implied investment management styles and how such attributions evolve along the set of dominant portfolios?. To answer the first question, we estimate the complete set of portfolios that are first- and second-degree stochastically dominant versus the benchmark using modified optimization techniques developed by Scaillet and Topaloglou (2010). For the first degree stochastic dominance efficiency, we solve mixed integer optimization programs. For the second degree stochastic dominance efficiency, we solve linear optimization programs. Thus, we apply for first time in the literature the concept of Stochastic Dominance Efficiency on a global scale portfolio optimization problem. Our choice to apply such methods to privatisation portfolios is unique in the finance literature. Subsequently, to answer the second question for the finite set of estimated portfolios, we perform robust Bayesian estimation of their exposure to investment management styles captured by factor mimicking portfolios approximating Value, Growth, Size and Debt Leverage. This is performed using Monte Carlo Integration along the lines of Kloek and van Dijk (1978) and van Dijk and Kloek (1980) in the context of Sharpe (1992).

Our evidence reveals a significant number of portfolios which first- and second-degree stochastically dominate the market benchmark, typically smooth and stable, overweighting non-Cyclical and non-Strategic assets. We also observe rotation of portfolio weights across business cycles reflecting better performance of small size companies and large privatization transactions signalling less state control. Moreover, Growth style frequently drives portfolio returns during the first business cycle from 1985 to 1994 which is in contrast with the international evidence for conventional equity portfolios, which then rotates to Growth and a balanced mix of the remaining styles driving returns during the cycle from 1995 to 2003. Size style leads returns during the last business cycle, from 2004 to 2012, a result in agreement with the international evidence, see Perez-Quiros and Timmermann (2000). Finally, Value appears as the least important style in all periods, a result in contrast with the broader international evidence on conventional equity portfolios but consistent with more recent evidence.

The plan of the paper is as follows. In Section 2 we provide a brief review of the literature over the last two decades, in Section 3 we outline our stochastic dominance optimization procedures, our data set and the respective portfolio selection results. In Section 4 we outline our robust Bayesian performance attribution methods, the construction of investment style factor mimicking portfolios and the associated empirical results. In section 5 we offer some discussion and concluding remarks.

2. Stochastic Dominance Efficiency in the Global Privatization Portfolio

The Markowitz (1952) mean-variance approach is a seminal contribution to portfolio selection, however it is based on a number of restrictive assumptions regarding the data and investor preferences and presents error-maximising properties leading to extreme solutions. Moreover, variance is a popular risk measure but it is associated with a restricted class of preferences and probability distributions and is not robust to outliers (extreme deviations are greatly over-weighted and small deviations are relatively neglected). This is a fundamental problem in the mean-variance approach and it is also the reason why this approach, unlike most decision theories, does not have a natural preference foundation.

Young (1998) uses the minimum historical return as a measure of risk, and generates optimal portfolios that minimize the maximum loss over all past observations, for a given level of return. Yamazaki and Konno, (1991) propose the mean absolute deviation as a measure of risk, resulting in optimal portfolios as a solution of linear optimization problems. Rockafellar and Uryasev (2000) propose the Conditional-Value-at-Risk (CvaR), which is the conditional expectation of losses exceeding the Value-at-Risk (VaR), as an alternative risk measure for portfolio selection. Alexander and Baptista (2004) compare the performance of VaR and CvaR on portfolio selection with the Mean-Variance model. A complete review of risk measures is contained in the paper by Frittelli and Rosazza Giannin (2002).

It is well known that asset returns cannot be described by mean and variance alone. For example, the monthly returns of many stocks exhibit positive skewness and excess kurtosis. Also, a wealth of psychological research on decision-making under uncertainty suggests that risk cannot be described by variance. Especially the phenomena of skewness preference and loss aversion have attracted much attention among financial economists. This provides a rationale for replacing the MV and other currently used parametric risk-return criteria with a more general efficiency criterion that accounts for higher-order central moments (such as skewness and kurtosis). We manage to do so by employing a stochastic dominance (SD) methodology.

Stochastic dominance introduced by Quirk and Saposnik (1962) and further developed by Hadar and Russell (1969), Hanoch and Levy (1969), Rothschild and Stiglitz (1970), and Whitmore (1970), is a useful concept for analyzing risky decision making when partial information regarding the decision maker's risk preferences is available. The theoretical attractiveness of SD lies in its nonparametric nature. SD criteria do not require a full parametric specification of the preferences of the decision maker and the statistical distribution of the choice alternatives, but rather they rely on a set of general assumptions. The first order stochastic dominance criterion places on the form of the utility function no restriction beyond the usual requirement that it is non-decreasing, i.e., investors prefer more to less. (Bawa, 1975). Thus, this criterion is appropriate for both risk averters and risk lovers since the utility function may contain concave as well as convex segments. Owing to its generality, the first order stochastic dominance permits a preliminary screening of investment alternatives eliminating those, which no rational investor will ever choose. The second order stochastic dominance criterion adds the assumption of global risk aversion.

Optimization of investment portfolios is an interesting application area for SD because, first, economic theory does not provide us with strong predictions about investor preferences and asset return distributions, and second, nonparametric analysis can be benefit from large data sets that are now available. Still, the focus of the research in this area has predominantly been on mean-variance approach (MV). Unfortunately, MV is consistent with expected utility theory only in the case where investor preferences and return distributions obey highly restrictive conditions (see, e.g., Hanoch and Levy 1969, Levy 1992). The main disadvantage of the mean-variance approach is that it allows for violations of first-order stochastic dominance, since it is not robust to outliers.

An important reason why SD has not been applied before in the construction of optimal portfolios is the restriction that until recently, stochastic dominance could only be tested pair-wise. Thus, we could only compare the return distribution of asset A over asset B, with respect to the SD criteria. Barret and Donald (2003) proposed a consistent bootstrap test, for the special case of independent prospects, and showed that it has an asymptotically exact size on the least favorable points in the null hypothesis. Linton, Maasoumi, and Whang (2005) provide a comprehensive theory of inference for a class of test statistics for the standard pairwise comparison of prospects. Their null hypothesis is of stochastic maximality in a finite set, i.e., that there is at least one prospect that weakly stochastically dominated some of the others. The alternative is two-sided and the number of prospects considered is finite. Because this only involved pairwise comparison it is not appropriate for the situation where an investor may combine a set of basis assets into a portfolio. Other SD tests has been suggested in the literature; see e.g. Anderson (1996), Beach and Davidson (1983), Davidson and Duclos (2000). However these tests rely on pairwise comparisons made at a fixed number of arbitrary chosen points. This is not a desirable feature since it introduces the possibility of test inconsistency.

The portfolio problem is especially difficult, because we have to consider infinitely many portfolios, while the standard SD rules rely on pairwise comparison of the individual alternatives. Recently, there has been signifficant progress on computational and statistical issues that have advanced the position of the stochastic dominance method, introducing the notion of Stochastic Dominance Efficiency. This notion is a direct extension of stochastic dominance to the case where full diversification is allowed. This means that we can now compare the return distribution of any portfolio that can be constructed from a set of assets, with another portfolio.

Post (2003) and Post and Versijp (2007), propose tests of the same hypothesis and provide a method of inference based on a duality representation of the investor's expected utility maximization problem. Their procedure relies on ranked observations in an i.i.d. framework. Kuosmanen (2004) develop linear programming tests for SD efficiency that do account for diversification possibilities. Although these tests provide an important step in the evolution of the SD methodology, they rely intrinsically on using ranked observations under iid assumption on the asset returns. Contrary to the initial observations, ranked observations, i.e., order statistics, are no longer iid.

Scaillet and Topaloglou (2010) develop consistent tests for SDE at any order for time-dependent data. Serial correlation is known to pollute financial, and to alter, often severely, the size and power of testing procedures when neglected. They rely on Kolmogorov-Smirnov type tests inspired by the consistent procedures developed by Barrett and Donald (2003), testing for SD. They develop general SD efficiency tests that compare a given portfolio with an optimal diversified portfolio formed from a given finite set of assets. They build on the general distribution definition of SD in contrast to the traditional expected utility framework.

The concept is used in numerous empirical studies and practical financial applications; see for example, Lozano and Gutierrez (2008), Dupacova and Kopa (2012), Lizyavev and Ruszczynski (2012). Kopa and Post (2013) represent the general N-th order SD criterion by using general picewise-polynomial functions that are linear in the parameters.

In spite of these attractive features of SD Efficiency versus more traditional portfolio selection techniques, one might still question our choice on the basis of the strictness of the dominance criterion applying to all utility functions in a given class, even to those that describe extreme preferences which rarely represent investor behaviour and violate SD predictions. Leshno and Levy (2002) established the concept of Almost Stochastic Dominance (ASD), formalising rules which exhibit a preference structure for most decision makers, but not for all of them, thus allowing for accommodation of a number of perspectives. Tzeng et al (2013) show a counterexample to the main results of Leshno and Levy and provide a new definition of Almost Second-Degree Stochastic Dominance which is shown to be necessary and sufficient condition to rank asset return distributions for all decision makers excluding extreme preferences. Although both Leshno and Levy and Tzeng approaches contribute a breakthrough in the stochastic dominance literature, Xu (2013) shows that the former exhibits the hierarchy property but not the expected-utility maximization, while the latter exhibits the expected-utility maximization but not the hierarchy property. Unfortunately, empirical applications of ASD, such as estimation of portfolios or portfolios that dominate a benchmark portfolio, are computationally prohibitive because of the structure of the ASD concept, see Lizyayev and Ruszczynski (2012).

The above papers test for weaker versions of the aforementioned notions of stochastic dominance. More specifically, they allow a portfolio A to be FSD (SSD) efficient if and only if it is not dominated by any other portfolio constructed from a set of assets. Thus, portfolio A is efficient, if and only if there exists an increasing (concave) utility function that rationalizes the optimal choice of A over any other portfolio.

In this paper we develop a stochastic dominance methodology to determine whether asset allocation decisions on Strategic vs. non-Strategic and Cyclical vs. non-Cyclical asset classes improve the feasible choices for non-satiable and risk-averse decision makers. For our initial portfolio selection we opt for stochastic dominance procedures as proposed by Scaillet and Topaloglou (2010) who use SD Efficiency techniques that can compare a given benchmark portfolio with an optimal diversified portfolio constructed from a set of assets.

In contrast, Scaillet and Topaloglou (2010) use a stronger version of stochastic dominance efficiency. In this paper, we adopt the SDE definition of Scaillet and Topaloglou (2010), where a portfolio is defined to be SD efficient when it stochastically dominates all other portfolios for any given SDE criterion under consideration. If a portfolio dominates all other portfolios then it is not dominated by any other portfolio, thus it is SD efficient. The Scaillet and Topaloglou (2010) SDE methodology is more general than the previous SDE methodologies in that it does not assume that asset returns are independent and identically distributed.

We use the Scaillet Topaloglou test, motivated by the assumption that an investor being uncertain of the exact form of her utility function, needs to have a test of whether a given portfolio can be considered as an optimal choice for any given utility function. Thus, we test for global optimality rather than using first-order conditions.

We test whether we can construct optimal portfolios of Strategic vs. non-Strategic and Cyclical vs. non-Cyclical assets that dominate the benchmark portfolio with respect to the first and second stochastic dominance criteria.

2.1 Stochastic Dominance Efficiency

We consider a process $\{\mathbf{Y}_t; t \text{ in } Z\}$ taking values in R^2. The observations consist of a realization of $\{\mathbf{Y}_t ; t = 1,...,T\}$. These data correspond to observed returns of the different investment alternatives (that is, Strategic and non-Strategic, or Cyclical and non-Cyclical asset returns). We denote by $F(\mathbf{y})$, the continuous cdf of $\mathbf{Y}=(Y_1,Y_2)'$ at point $\mathbf{y}=(y_1,y_2)'$.

Let us consider a portfolio $\boldsymbol{\lambda}$ in L, where $L = \{\boldsymbol{\lambda} \text{ in } R_+^2 : \mathbf{e}' \boldsymbol{\lambda}=1\}$ with $\mathbf{e}$ being a vector of units. This means that short sales are not allowed and that the portfolio weights sum to one.

Let us denote by $G(z,\boldsymbol{\lambda};F)$ the cumulative density function (cdf) of the portfolio return $\boldsymbol{\lambda}'\mathbf{Y}$ at point z given by

$$G(z,\boldsymbol{\lambda};F) := \int_{R^n} I(\lambda' u \leq z)dF(u) \tag{1}$$

where I( ) denotes the indicator function taking the value of 1 if $\lambda' u \leq z$ and 0 otherwise.

Further, define

$$\begin{aligned} &J_1(z,\lambda;F) := G(z,\lambda;F), \\ &J_2(z,\lambda;F) := \int_{-\infty}^{z} G(u,\lambda;F)du = \int_{-\infty}^{z} J_1(u,\lambda;F)du \end{aligned} \tag{2}$$

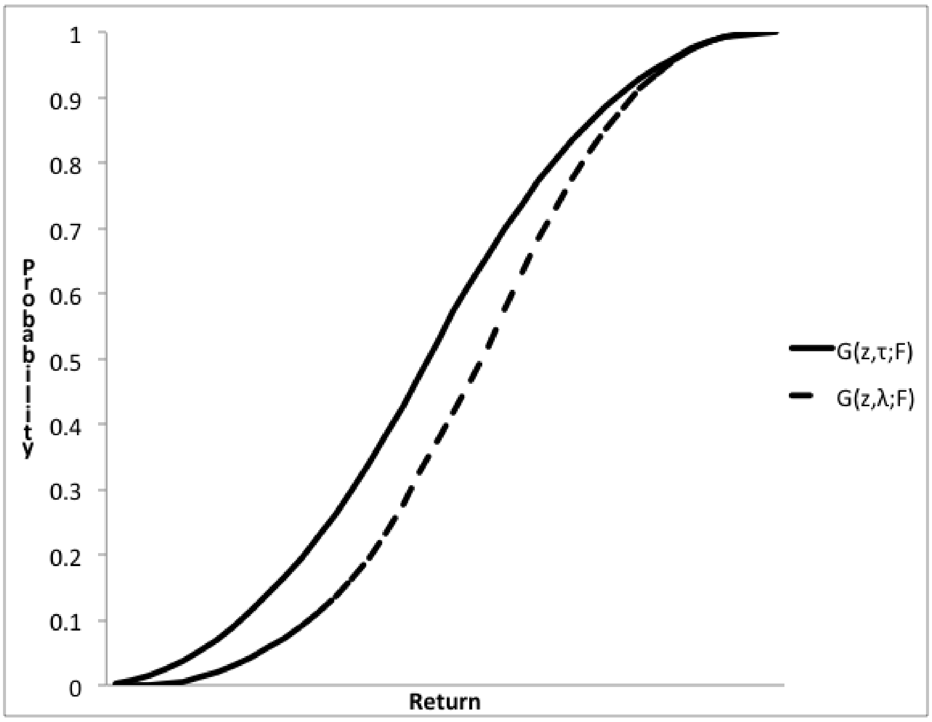
2.2 Portfolio construction under stochastic dominance efficiency criteria

In this section, we describe the two SDE criteria we employ, their respective mathematical programming formulations and the way we apply the Scaillet and Topaloglou (2010) statistical test to construct optimal portfolios.

2.2.1 Mathematical Formulation for FSDE

The distribution of portfolio $\boldsymbol{\lambda}$ dominates the distribution of the benchmark portfolio $\boldsymbol{\tau}$ stochastically at first-order (FSD) if, for any argument z, $J_1(z,\boldsymbol{\tau};F) > J_2(z,\boldsymbol{\lambda};F)$. If the portfolio $\boldsymbol{\lambda}$ dominates the benchmark $\boldsymbol{\tau}$ at first order, then the returns in $\boldsymbol{\tau}$ are always lower that $\boldsymbol{\lambda}$, so that $\boldsymbol{\lambda}$ is preferable. Figure 1 displays the first stochastic dominance of portfolio $\boldsymbol{\lambda}$ over the market portfolio $\boldsymbol{\tau}$.

Figure 1. First-degree stochastic dominance efficiency of portfolio λ over the market portfolio τ.



The objective function that we use is the following:

$$\mathrm{Max}_{z,\lambda}[G(z,\tau;F)-G(z,\lambda;F)] \qquad (3)$$

The above maximization specification results in the optimal portfolio $\boldsymbol{\lambda}$ constructed from the set of alternative investment assets that reach the highest return for a given probability. The first order stochastic dominance criterion places on the form of the utility function no restriction beyond the usual requirement that it is non-decreasing monotonic function of z, i.e., when U' (z) ≥ 0, in which case investors prefer more to less. Thus, this criterion is appropriate for both risk averters and risk lovers since the utility function may contain concave as well as convex segments. Owing to its generality, the first order stochastic dominance permits a preliminary screening of investment alternatives eliminating those which no rational investor will ever choose.

To solve the problem described by equation (3), we discretize the variable z and we solve smaller problems P(r) in which z is fixed to a given return r (see Scaillet and Topaloglou 2010 for the proof and the derivation of the optimization problem). Then, we take the value for z that yields the maximum distance in equation (3). Hence, the problem boils down to the following MIP minimization problem.

$$
\begin{array}{l}
\min \ {}_{t=1}^{T} W_t \\
s.t. \\
M(W_t \quad 1) \quad r \qquad Y_t \quad MW_t \\
e \quad = 1, \\
\quad\ 0, \\
W_t \quad \{0,1\}, \quad t
\end{array}
\tag{4}
$$

The model is a mixed integer program minimizing the sum of all binary variables W_t. According to the first set of inequalities, W_t equals 1 for each scenario t for which $r \geq \lambda' Y_t$, and 0 otherwise. The following equation defines the sum of all weights to be unity, while the last inequality disallows negative weights. For the optimal solution, which involves 60 mixed integer optimisation programs, it takes less than thirty minutes. These linear problems have always feasible solutions. The problems are optimized with Gurobi solver on an iMac with 4*2.93 GHz Power, 16 GB of RAM. The Gurobi solver uses the branch and bound technique. The optimization problems are modeled using GAMS (General Algebraic Modeling System).

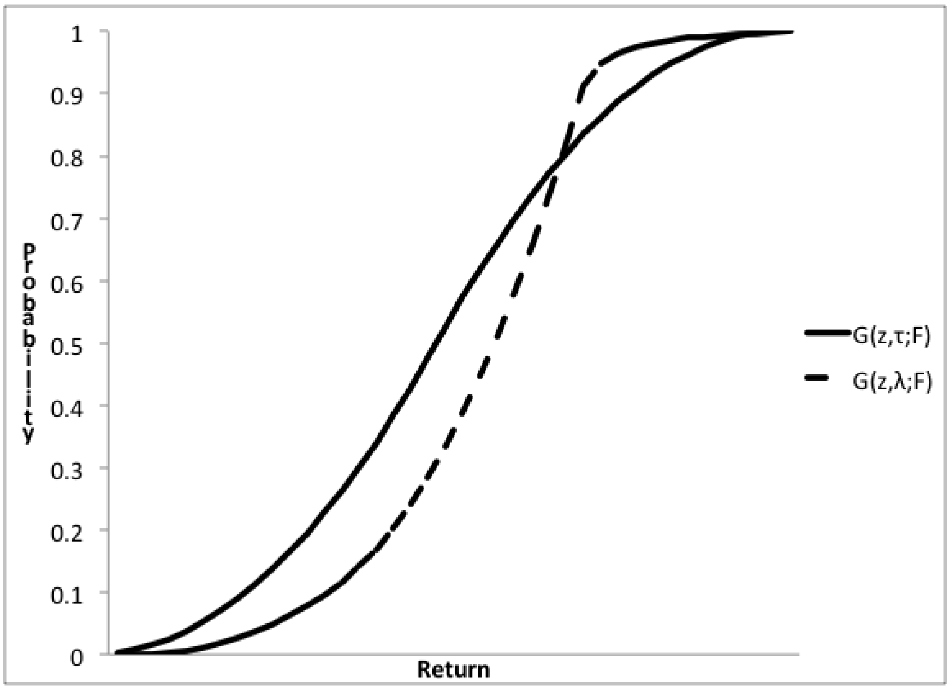
FSD is a sufficient but not a necessary condition for second-order stochastic dominance (SSD).

2.2.2 Mathematical Formulation for SSDE

For SSD the objective function that we use is the following:

$$\mathrm{Max}_{z,\lambda}[\int_{-\infty}^{z} G(u,\tau;F)du - \int_{-\infty}^{z} G(u,\lambda;F)du] \tag{5}$$

Figure 2. Second-degree stochastic dominance efficiency of portfolio λ over the market portfolio τ.



The second order stochastic dominance criterion adds the assumption of global risk aversion, in which case the utility function is non-decreasing monotonic and concave function of z, i.e., U' (z) ≥ 0, and U'' (z) ≤ 0. This criterion is based on a stronger assumption and therefore, it permits a more sensible selection of investments. The model for second order stochastic dominance efficiency is formulated in terms of standard linear programming. Numerical implementation of first order stochastic dominance efficiency is much more difficult since we need to develop mixed integer programming formulations.

Again, according to Scaillet and Topaloglou 2010, we trasform model (5) into the following linear program, which is very easy to solve:

$$
\begin{aligned}
& Min \quad {}^{T}_{t=1} W_t \\
& s.t. \\
& W_t \quad r \qquad Y_t, \quad t \\
& e \quad = 1, \\
& \quad\;\; 0 \\
& W_t \quad 0, \quad t
\end{aligned}
\tag{6}
$$

According to the first set of inequalities, W_t equals r - $\lambda' Y_t$ for each scenario t for which r ≥ $\lambda' Y_t$, and 0 otherwise. The following equation defines the sum of all weights to be unity, while the last inequality disallows negative weights.

For the optimal solution, which involves 60 linear optimization programs, it takes less than one minute. These linear problems have always feasible solutions. The problems are optimized with Gurobi solver again. Fabian et al (2011) suggest algorithmic improvements for stochastic optimization problems with second stochastic dominance constraints based on dual formulations. Robustness analysis of dominance relationships traditionally focuses on the dual formulation; see for example, Dentcheva and Ruszczynski (2010), and Liu and Xu (2013).

2.3 The Global Privatization Portfolio

We consider the total number of privatisations deals across the globe that is available in the SDC Merger and Acquisition database. Our initial sample covers all deals of the period from 1985 to 2012, for which the database reports a total number of about 62,000 privatization transactions on listed assets. Privatization transactions that take place off-stock exchange, through "trade-sales", are less transparent and their data are more difficult to collect, thus they are not included in our sample. However, at this point we need to clarify that the choice of privatization method does not relate to the quality of the deal, but rather reflects a plethora of parameters that a policy maker has to take into account. For example, current market conditions may not be favourable for asset sales through the stock market, or the government policy requires the exclusion of financial investors and attraction of specialist investors within asset's industry sector. To be included in our sample we require information on announcement date, transaction value and share prices to be available. This filtration left us with a sample of 7855 deals across the globe for 67 countries, which concerns the majority of the listed privatized assets across countries. Subsequently, we used Datastream to collect information on share prices and other variables for each target company as well as the corresponding national market benchmark from the date of privatization transaction to 2012. We characterise the companies in our sample by their countries of origin and sectors and also collect information on the sector of the acquirer firm. Using this information, we classify the data in two ways. First, when a target company belongs to the same sector as the acquirer company we characterise this as a strategic investment, so we have a distinction between Strategic versus non-Strategic investments, see OECD (2010), Czerny et al. (2014). Second, we use the Datastream classification to identify companies belonging to cyclical sectors, so we have a second distinction of Cyclical versus non-Cyclical assets, see Morningstar (2011), J.P.Morgan (2012), and Lebovitz et al (2016). Thus, our aim is to construct our basic dataset so that we obtain for each country aggregate fund returns for Strategic vs. non-Strategic and Cyclical vs. non-Cyclical transactions.

Due to the long horizon of privatization investments, we consider a buy-and-hold strategy of a global investor who invests in country privatization funds versus the market benchmark. For each country, we measure the return of each asset from the privatization transaction date to the end of a predefined sample sub-period, which is an event-to-date return as in Spiess and Aflek-Graves (1995) and Cochrane (2005). Then we aggregate the annualised returns of assets within each country fund for the respective sub-period of the full sample 1985-2012. For Strategic versus non-Strategic investments the four sub-samples are defined as 1985-1995, 1996-1998, 1999-2003 and 2004-2012 periods. For Cyclical versus non-Cyclical investments our sub-periods correspond to 1985-1994, 1995-1998, 1999-2003 and 2004-2012 respectively. The setting of sub-periods differs slightly between the two classification schemes because of the relatively low frequency of transactions for some countries in the 1980's and our requirement that at least one transaction is available for each country in each sub-period. Moreover, this condition also forced us to aggregate over some peripheral countries, thus eliminating the effects of possible idiosyncratic factors. In particular, for the Strategic versus non-Strategic classification we combine in three cases, namely Estonia, Ukraine and Kazakhstan; Jordan, Oman and United Arab Emirates; and Thailand and Vietnam. This aggregation leads to a sample of 62 countries. Similarly, for the Cyclical versus non-Cyclical classification we combine in six cases, namely Czech Republic and Hungary; Estonia, Ukraine and Kazakhstan; Ghana and Nigeria; India and Sri Lanka; Jordan, Oman and United Arab Emirates; and Morocco and Tunisia. Thus, for the latter classification we are left with 59 countries with complete data[4]. We observe that the chosen country aggregations do not fully coincide for our Cyclical-non Cyclical and the Strategic-non Strategic allocations, while sample sub-periods are also of unequal length. These choices have been dictated by the limitations of the database and the need to fulfil the requirement that at least one transaction should fall within each country-period grid. However, our sample sub-periods tend to agree with the different phases of the global business cycle factor as estimated by Kose et al (2012). In particular, the period from 1985 to 2012 covers roughly three full cycles, where our first sub-sample corresponds roughly to a full cycle, our second sub-sample corresponds to a period of moderate expansion, our third sub-sample corresponds to a recession, and finally our fourth sub-sample corresponds roughly to a full cycle. Due to large number of privatization transactions that took place since 1995 and for the subsequent years, we have been able to split the second cycle in two sub-periods.

In the following we provide some details explaining how the aggregate returns are calculated over the respective sub-periods. For each transaction we assume a holding period from its inception until the end of the sample sub-period. Any transactions that took place during the first (second) half of a particular year are considered as if they took place at the beginning (end) of the year. As an example,

[4] The full list of countries participating in our two alternative classifications is available to the reader upon request.

suppose that for a given country the sample sub-period concerns from 1993 to 1998, over which we observed four privatisation transactions (1993, 1995, 1997 and 1998), which all took place at the beginning of the respective year. We calculate the annualised return for each transaction over the respective holding period; that is, from 1993 to 1998 for the first transaction, from 1995 to 1998 for the second transaction, from 1997 to 1998 for the third transaction and from the beginning until the end of 1998 for the last transaction.

Annualizing the returns allow us to compare returns across different periods. Subsequently, we aggregate annualised returns across transactions within each country fund using three different weighting schemes: equal weighting, asset market value weighting and transaction value weighting. This choice results in three different portfolios, each reflecting a different emphasis on asset characteristics: the relative size of the asset in the market, the relative size of the privatization transaction or no distinction between assets. We use the same approach to compute benchmark returns, for each country in the respective time periods, where equally weighted aggregation now takes place across all assets that participate in the country's general index. We present the properties of the empirical distributions of our return data in Figures 3.1-3.3 in the Appendix, showing clearly non-normality of the data as well as substantial differences between asset classes, which further justifies our choices for the study of particular asset classes and the use of non-parametric methods.

2.4 Empirical Results

In Tables 1 and 2 we present the average estimation results for our twelve Cyclical vs. non-Cyclical and the twelve Strategic vs. non-Strategic portfolio allocation cases. The lines exhibit the optimal portfolios by the method of calculating country fund returns, while the columns exhibit the optimal portfolios by period. The results suggest strongly that in general we can construct portfolios of Cyclical versus non-Cyclical funds or Strategic versus non-Strategic funds that dominate the market benchmark.

Table 1 presents results for Cyclical vs. non-Cyclical funds, where we observe that for seven out of twelve allocations it is possible to construct portfolios that both first- and second-degree stochastically dominate (FSD, SSD) the market benchmark, in two cases there exist portfolios that only FSD the market benchmark, while in three cases there is no dominant privatization portfolio. In particular, the market benchmark dominates market value-weighted return privatization portfolios in the period 1995-1998, which is a period of economic expansion over which greater exposure to large market value assets cannot outperform the market. Moreover, the market benchmark dominates both market value-weighted and transaction value-weighted return privatization portfolios in the period 2004-2012, which is a period covering a full business cycle over which overexposure to large assets and large transactions cannot outperform the market. In two cases we observe only FSD portfolios, in 1995-1998 for equally-weighted returns and in 1999-2003 for market value-weighted returns, showing that in these cases the market benchmark portfolio is SSD efficient.

Table 1. Cyclical vs. non-Cyclical Portfolio Allocations

		1985-1994		1995-1998		1999-2003		2004-2012	
		FSD	SSD	FSD	SSD	FSD	SSD	FSD	SSD
EW Returns	Dominant Portfolios	14	27	26	Benchmark	59	59	41	45
	Cyclical Weight	0.09	0.07	0.84	-	0.51	0.53	0.11	0.19
	Non-Cyclical Weight	0.91	0.93	0.16	-	0.49	0.47	0.89	0.81
MVW Returns	Dominant Portfolios	52	46		Benchmark	21	Benchmark	Benchmark	
	Cyclical Weight	0.02	0.02		-	0.04		-	
	Non-Cyclical Weight	0.98	0.98		-	0.96		-	
TVW Returns	Dominant Portfolios	50	59	50	11	59	59	Benchmark	
	Cyclical Weight	0.09	0.10	0.97	0.99	0.22	0.40	-	
	Non-Cyclical Weight	0.91	0.90	0.03	0.01	0.78	0.60	-	

Note: The table presents the number of dominant portfolios and their average weights. EW, MVW and TVW denote Equally Weighted, Market-Value Weighted and Transaction Value-Weighted respectively. FSD and SSD denote the first- and second-degree stochastically dominant privatization portfolios respectively over the market benchmark. “Benchmark” means that there is no privatization dominance at any order.

Table 1 also presents the average weights of FSD and SSD portfolios, while Figures 4-6 present graphically the detailed evolution of weights for all estimated portfolios ranked from most efficient to least efficient. The general picture reveals strong overweighting of non-Cyclical versus Cyclical privatization funds for all periods except 1995-1998 for which emphasis is placed on Cyclical assets, suggesting that over the full course of a business cycle (1985-1994, 2004-2012) but also in recessionary periods (1999-2003) it is possible to construct portfolios emphasising non-Cyclical assets to outperform the market. However, during economic expansion (1995-1998) portfolios have to overweight Cyclical assets to be able to outperform the market.

The rotation of portfolio weights exhibits different characteristics across different country fund types. In particular, during the first business cycle all country fund types exhibit non-Cyclical dominant portfolios, of which equally-weighted and transaction value-weighted portfolios subsequently switch to Cyclical assets to benefit from the booming period of the next business cycle. This switch is optimal for FSD but not SSD, except of transaction value-weighted funds, showing that large privatizations tend to exhibit higher return and lower volatility leading to outperformance. This result is consistent with evidence suggested by Dyck and Zingales (2004) where controlling block sales of state assets generate superior results. These results are reversed, as expected, during the recession phase of the second business cycle but to a different degree for different country fund types. During the third business cycle, we observe dominance of the market benchmark portfolio for size-driven country funds, pointing that the reappearance of non-Cyclical dominant portfolios in equally-weighted country funds is primarily attributed to the performance of small companies.

Reviewing the evolution of portfolio weights in Figures 4-6, we observe a number of convergence and divergence patterns between FSD- and SSD-efficient portfolios, as well as a remarkable stability of SSD portfolios over FSD to maintain dominance over the market benchmark. For equally-weighted return portfolios in the periods 1985-1994 and 2004-2012, which cover two distant business cycles, we observe that FSD and SSD portfolios converge for high levels of dominance and start diverging for lower levels, as FSD captures higher returns per unit of risk faster than SSD which penalises for risk. A different picture is revealed in the period 1999-2003, where higher efficiency portfolios start with divergence and then tend to converge for lower levels and reverse the weighting scheme. Given the stability of the weighting schemes for market value-weighted and transaction value-weighted returns, which emphasise the effects of size, it is likely that this weighting scheme reversal reflects strong return characteristics effects from smaller companies.

Table 2 presents results for Strategic versus non-Strategic funds, where we observe that in seven out of twelve allocations it is possible to construct portfolios that both first- and second-degree stochastically dominate (FSD, SSD) the market benchmark, while in the rest five cases there is no dominant privatization portfolio. In particular, the market benchmark is dominant during the expansion period of 1996-1998 both equally-weighted and market value-weighted return privatization portfolios, and is outperformed by FSD and SSD portfolios only in the case of portfolio returns emphasising large privatization transactions. Moreover, as in Table 1, the market benchmark dominates both market value-weighted and transaction value-weighted return privatization portfolios in the period 2004-2012, so overexposure to large assets and large transactions cannot outperform the market. Finally, the market benchmark dominates all market value-weighted privatization portfolios, with the exception of the recession period 1999-2003, which provides dominant privatization portfolios for all return types.

Table 2. Strategic vs. Non-Strategic Portfolio Allocations

		1985-1995		1996-1998		1999-2003		2004-2012	
		FSD	SSD	FSD	SSD	FSD	SSD	FSD	SSD
EW Returns	Dominant Portfolios	58	62	Benchmark		62	62	17	12
	Strategic Weight	0.10	0.19	-		0.27	0.17	0.88	0.78
	Non-Strategic Weight	0.90	0.81	-		0.74	0.83	0.12	0.22
MVW Returns	Dominant Portfolios	Benchmark		Benchmark		18	62	Benchmark	
	Strategic Weight	-		-		0.02	0.20	-	
	Non-Strategic Weight	-		-		0.98	0.80	-	
TVW Returns	Dominant Portfolios	59	62	41	61	62	62	Benchmark	
	Strategic Weight	0.32	0.90	0.05	0.08	0.4	0.4	-	
	Non-Strategic Weight	0.68	0.10	0.95	0.92	0.6	0.6	-	

Note: The table presents the number of dominant portfolios and their average weights. EW, MVW and TVW denote Equally Weighted, Market-Value Weighted and Transaction Value-Weighted respectively. FSD and SSD denote the first- and second-degree stochastically dominant privatization portfolios respectively over the market benchmark. "Benchmark" means that there is no privatization dominance at any order.

As in the previous case, Table 2 also presents the average weights of FSD and SSD portfolios, while Figures 7-9 present graphically the detailed evolution of weights for all estimated portfolios ranked from most to least efficient. The general picture reveals strong overweighting of non-Strategic versus Strategic privatization funds, irrespective of cycle period and return definition. Strategic assets are overweighed only in periods 2004-2012 for equally weighted returns, signifying the effect of small companies as in the case of Cyclical versus non-Cyclical allocations, as well as in the case of period 1985-1995 for transaction value-weighted returns. The latter case develops a disagreement between FSD and SSD results, where FSD is captured by aggressive return characteristics irrespective of risk and is lead to weighting scheme reversal to maintain dominance over the market benchmark.

The rotation of portfolio weights exhibits known but simpler patterns across different country fund types as compared to Cyclical vs. non-Cyclical allocations. In particular, we observe a stable presence of non-Strategic dominant portfolios for equally-weighted and transaction value-weighted country funds during the first two business cycles. Moreover, we observe portfolio weights of equally-weighted country funds switching towards Strategic portfolios during the third business cycle, a result attributed to the performance of small companies as in the case of Cyclical vs. non-Cyclical allocations. Finally, our evidence suggests that the effect of large privatizations is also present in this type of allocations, allowing for the selection of dominant portfolios over the market benchmark signalling higher performance of assets with less state control.

Our cross-sectional evidence suggests clearly the existence of portfolios that beat the benchmark under very unrestrictive conditions. To verify our initial findings, we also pursue in-sample performance evaluation[5] analysis through Sharpe Ratio and U-P Ratio statistics for our average dominant asset allocations of Table 1 and 2, subject to transaction costs. Our findings are presented in Table 3 and Table 4 and are fully consistent with our evidence on dominant portfolios, suggesting the superiority of our portfolio choice over the benchmark.

Table 3. Sharpe Ratio for Asset Allocations (p-values in parentheses)

		1985-1995		1996-1998		1999-2003		2004-2012	
		FSD	SSD	FSD	SSD	FSD	SSD	FSD	SSD
EW Returns	Strategic vs non-Strategic	0.205 (0.000)	0.185 (0.000)	-	-	0.323 (0.000)	0.305 (0.000)	-0.037 (0.000)	-0.069 (0.000)
	Cyclical vs non-Cyclical	0.328 (0.000)	0.326 (0.000)	-0.092 (0.000)	-	0.238 (0.000)	0.236 (0.000)	-0.180 (0.000)	-0.183 (0.000)
	benchmark	-1.781	-1.781	-0.895	-0.895	-3.082	-3.082	-0.507	-0.507
MVW Returns	Strategic vs non-Strategic	-	-	-	-	0.013 (0.000)	-0.007 (0.000)	-	-
	Cyclical vs non-Cyclical	0.220 (0.000)	0.221 (0.000)	-	-	-	0.006 (0.000)	-	-
	benchmark	-2.102	-2.102	-1.005	-1.005	-3.233	-3.233	-0.530	-0.530
TVW Returns	Strategic vs non-Strategic	0.164 (0.000)	0.179 (0.000)	0.011 (0.000)	-0.010 (0.000)	0.794 (0.000)	0.791 (0.000)	-	-
	Cyclical vs non-Cyclical	0.637).000)	0.631 (0.000)	0.134 (0.000)	0.142 (0.000)	0.693 (0.000)	0.723 (0.000)	-	-
	benchmark	-1.754	-1.754	-0.886	-0.886	-3.041	-3.041	-0.503	-0.503

Table 4. U-P Ratio for Asset Allocations (p-values in parentheses)

	1985-1995	1996-1998	1999-2003	2004-2012

[5] Out-of-sample performance analysis would require the construction of trading rules and the use of substantial time series data which are unavailable in the context of privatization portfolios.

		FSD	SSD	FSD	SSD	FSD	SSD	FSD	SSD
EW Returns	Strategic vs non-Strategic	0.830 (0.000)	0.761 (0.000)	-	-	1.855 (0.000)	2.040 (0.000)	-0.065 (0.000)	-0.124 (0.000)
	Cyclical vs non-Cyclical	1.910 (0.000)	1.902 (0.000)	-0.281 (0.000)	-	1.026 (0.000)	1.007 (0.000)	-0.253 (0.000)	-0.267 (0.000)
	benchmark	-1.960	-1.960	-1.276	-1.276	-4.136	-4.136	-0.964	-0.964
MVW Returns	Strategic vs non-Strategic	-	-	-	-	0.027 (0.000)	-0.009 (0.000)	-	-
	Cyclical vs non-Cyclical	1.040 (0.000)	1.044 (0.000)	-	-	-	0.013 (0.000)	-	-
	benchmark	-2.018	-2.018	-1.369	-1.369	-4.302	-4.302	-0.914	-0.914
TVW Returns	Strategic vs non-Strategic	0.280 (0.000)	0.480 (0.000)	0.027 (0.000)	-0.011 (0.000)	3.710 (0.000)	3.711 (0.000)	-	-
	Cyclical vs non-Cyclical	2.001).000)	1.985 (0.000)	0.256 (0.000)	0.274 (0.000)	2.346 (0.000)	3.057 (0.000)	-	-
	benchmark	-1.929	-1.929	-1.260	-1.260	-4.086	-4.086	-0.960	-0.960

3 Global Privatization Investment Styles

Asset funds are typically characterized by their investment management style. In this section we examine the point of view of a global asset manager and apply robust procedures to determine the mixture of his/her investment styles. We perform return attribution analysis of our FSD and SSD privatization portfolios along the seminal work of Sharpe (1988, 1992), who attributes portfolio returns on a finite set of factors capturing investment management styles. The analysis effectively offers a breakdown of our initial asset allocations of Cyclical vs. non-Cyclical assets and Strategic vs. non-Strategic assets into investment style sub-portfolios characterised by debt leverage, size, value and growth features. This follows Fama and French (1992, 1993) who introduce value and size but also expands to characteristics capturing leverage and growth. Style investing was analysed in a decision making behavioural context by Barberis and Shleifer (2003) who introduced the "positive feedback effect" where an asset may start following an investment style once nominally classified as a follower of that style. Style analysis constitutes a popular approach to empirical portfolio performance measurement as applied by Brown and Goetzmann (1997), Kein and Madhavan (1997), Mass and Zhang (2009), Teo and Woo (2004), Boyer (2011) and Wahal and Yavuz (2013). The latter three studies present evidence in agreement with the Barberis ans Shleifer (2003) predictions.

3.1 Bayesian Sharpe Style Analysis

Sharpe Style Analysis attributes portfolio returns **y** on a finite set of factors X capturing investment management styles, such that

$$\begin{gathered} \boldsymbol{y} = X\boldsymbol{\beta} + \boldsymbol{u} \\ \text{s.t.} \\ \mathbf{1}'\boldsymbol{\beta} = 1 \text{ and } \boldsymbol{\beta} \geq 0 \end{gathered} \tag{7}$$

where **y** is a vector of N returns, X a matrix of N observations for K style factor returns, $\boldsymbol{\beta}$ is a vector of K style factor betas, **1** is a vector of units and the random variable $\boldsymbol{u} \sim N(\mathbf{0}, \sigma^2 I)$. The non-negativity constraint is useful, as it allows the beta coefficients to be interpreted as a vector of weights on investable indexes. However, the presence of inequality constraints for style factor beta coefficients introduces difficulties for least squares-based estimation in that the distributional properties of the estimates are not known. For this reason we view the above model from a Bayesian perspective and impose the parameter constraints in the form of information encapsulated in a prior distribution. Then, using the derived posterior distribution one can estimate moments and other functions of the style parameters by means of Monte Carlo Integration, introduced by Kloek and van Dijk (1978) and van Dijk and Kloek (1980).

We can impose the equality constraint by restating the above model in terms of deviations from one of the style factors, say the k-th, so that

$$\begin{gathered} \boldsymbol{y}^* = X^*\boldsymbol{\beta}^* + \boldsymbol{u}^* \\ \text{s.t.} \\ \boldsymbol{\beta}^* \geq 0 \end{gathered} \tag{8}$$

where the i-th elements of the restated variables are $y_i^* = y_i - x_{k,i}$ and $x_{l,i}^* = x_{l,i} - x_{k,i}$ for all $l \neq k$. The new vector $\boldsymbol{\beta}^*$ has K-1 elements and the K-th beta can be obtained from the imposed constraint $1 - \mathbf{1}'\boldsymbol{\beta}$. To be able to impose the inequality constraints we shall treat $\boldsymbol{\beta}^*$ as a random variable in population for which we have prior information in the form of inequality constraints, while we shall assume that all style factors in X^* are independent of each other and of $\boldsymbol{u}, \boldsymbol{\beta}^*$ and σ. Applying Bayes law, the joint posterior density of $\boldsymbol{\beta}^*$ and σ^2 can be written as

$$\text{Posterior}(\boldsymbol{\beta}^*, \sigma^2 | \boldsymbol{y}^*, X^*) = \text{Likelihood}(\boldsymbol{\beta}^*, \sigma^2 | \boldsymbol{y}^*, X^*) \times \text{Prior}(\boldsymbol{\beta}^*, \sigma^2) \tag{9}$$

The specification of the prior distribution will have an improper uninformative component about σ^2 and an informative one about $\boldsymbol{\beta}^*$ capturing the inequality constraint. Then, under normality assumption about $\boldsymbol{u}^*$, we can obtain an analytical form for the posterior distribution and generate random draws for the vector $\boldsymbol{\beta}^{*}$. We shall follow the Monte Carlo Integration approach of Kloek and van Dijk (1978) and van Dijk and Kloek (1980) to calculate the moments of style beta coefficients $\boldsymbol{\beta}^{*}$.

Following van Dijk and Kloek (1980) our prior distribution consists of (a) an improper uninformative component for σ^{2} and (b) an informative component for $\boldsymbol{\beta}^{*}$ which captures our prior knowledge embedded in the constraint $\boldsymbol{\beta}^{*} \geq 0$. Then, by independence we have

$$\text{Prior } \left(\boldsymbol{\beta}^{*}, \sigma^{2}\right) = \sigma^{-1}\ \mathrm{q}\left(\boldsymbol{\beta}^{*}\right) \tag{10}$$

where

Under the assumption of multivariate normality for $\mathbf{u}$, Judge et al (1985) show that the posterior density is a multivariate-t of the form

$$\text{Posterior } \left(\boldsymbol{\beta}^{*} \middle| \mathbf{y}^{*}, \mathrm{X}^{*}\right) = \mathrm{c}\left[\lambda + \frac{(\boldsymbol{\beta}^{*} - \mathbf{b})'\ \mathrm{X}'^{*}\ \mathrm{X}^{*}(\boldsymbol{\beta}^{*} - \mathbf{b})}{\hat{\sigma}^{2}}\right]^{-\frac{1}{2}(\lambda+\mathrm{K}-1)} \times \mathrm{q}\left(\boldsymbol{\beta}^{*}\right) \tag{11}$$

where

$$c = \frac{\lambda^{\frac{\lambda}{2}} \Gamma\left[\frac{1}{2}(\lambda + K - 1)\right]}{\pi^{\frac{K-1}{2}} \Gamma\left[\frac{\lambda}{2}\right] \det(\hat{\sigma}^{2}(X'^{*}X^{*})^{-1})^{\frac{1}{2}}}$$

λ denotes the degrees of freedom, $\Gamma(\,.\,)$ is the gamma function, is the OLS estimator of $\boldsymbol{\beta}^{*}$ and . The above equation is now of use in Monte Carlo Integration to calculate the posterior moments of $\boldsymbol{\beta}^{*}$ as introduced by Kloek and van Dijk (1978) and van Dijk and Kloek (1980). Assuming an Importance Function denoted $I\left(\boldsymbol{\beta}^{*}\right)$ which proxies the posterior density, then for any function $\mathrm{g}(\,.\,)$ and T random draws $\boldsymbol{\beta}_{1}^{*}, \boldsymbol{\beta}_{2}^{*}, \ldots, \boldsymbol{\beta}_{\mathrm{T}}^{*}$ from $I\left(\boldsymbol{\beta}^{*}\right)$, it can be shown that

$$\lim_{\mathrm{T}\to\infty} \frac{1}{\mathrm{T}} \sum_{\mathrm{i}=1}^{\mathrm{T}} \frac{\mathrm{g}\left(\boldsymbol{\beta}_{\mathrm{i}}^{*}\right) \text{Posterior } \left(\boldsymbol{\beta}_{\mathrm{i}}^{*} \middle| \mathbf{y}^{*} \mathrm{X}^{*}\right)}{\mathrm{I}\left(\boldsymbol{\beta}_{\mathrm{i}}^{*}\right)} = \mathrm{E}\left(\mathrm{g}\left(\boldsymbol{\beta}^{*}\right) \middle| \mathbf{y}^{*} \mathrm{X}^{*}\right) \tag{12}$$

which holds apart from a normalizing constant that can be calculated separately. This result suggests that we could use multivariate-t distribution as our Importance Function $I\left(\beta^{*}\right)$ to proxy the posterior distribution. Then our Monte Carlo Integration Estimator reduces to

$$\frac{1}{T}\sum_{i=1}^{T} g\left(\boldsymbol{\beta}_i^{*}\right) q\left(\boldsymbol{\beta}_i^{*}\right) \tag{13}$$

In implementing the above procedure we generate multivariate-t distributed vectors $\boldsymbol{\beta}_i^{*}$ following a standard procedure and set the number of replications equal to 10^5.

3.2 Construction of Factor Mimicking Portfolios

We approximate the true and unobservable investment style factors of debt leverage, size, value and growth by computing portfolios that mimic their behaviour. The four Factor Mimicking Portfolios (FMPs) are constructed for each country in our sample from 1985 to 2012. To construct each country's FMPs, we use all companies included in the market portfolio index, which is a proxy for the country's universe of assets. In each year for a given country, we compute company returns and rank them using each specific factor values, from largest to smallest, according to the factor definitions as described below:

Table 5.

Factor	Definition
$Debt\ Leverage_t$	$\frac{Total\ Debt\ per\ Share_t}{Book\ Value\ per\ Share_t}$
$Size_t$	$ln(Share\ Price_t \times Share\ Number_t)$
$Value_t$	$=\frac{DP_t+EP_t+SB_t+BP_t+CP_t}{5}$
$Growth_t$	$\frac{RE_t+EG_t}{2}$
Variable	Definition

DP_t	$\frac{Dividend_t}{Share\ Price_t}$
EP_t	$\frac{Earnings\ per\ Share_t}{Share\ Price_t}$
SB_t	$\frac{Net\ Sales\ per\ Share_t}{Share\ Price_t}$
BP_t	$\frac{Book\ Value\ per\ Share_t}{Share\ Price_t}$
CP_t	$\frac{Cash\ Flow\ per\ Share_t}{Share\ Price_t}$
RE_t	$\frac{Earnings\ per\ Share_t}{Book\ Value\ per\ Share_{t-1}}$
EG_t	$ln\frac{Book\ Value\ per\ Share_t}{Book\ Value\ per\ Share_{t-2}}$

We then construct each FMP, as an equally weighted hedge portfolio which is long the top quarter of the ranked returns and short the bottom quarter of the ranked returns of the corresponding factor. Then, for each style factor, we compute FMPs corresponding to the four periods (i.e. 1985-1995, 1996-1998, 1999-2003 and 2004-2012) in the same way as we constructed the benchmark portfolios. We use the same method to construct FMPs for all countries in our sample.

3.3 Empirical Results

In our empirical analysis we estimate the four style weights for the full set of efficient portfolios estimated in section 3 for Strategic vs. non-Strategic and Cyclical vs. non-Cyclical allocations. These include 613 FSD and 736 SSD portfolios, ordered from best to worst in terms of dominance strength. As our investment style allocations are estimated for a very large number of portfolios, we present arithmetic results in Table 6 only for the average of efficient portfolios in each of our 24 cases and opt to present the full set of style weights graphically in Figures 10-12 and 13-15 so that the reader can observe the evolution of style allocations for all portfolios ranked from best to worst. Figures 10-12 and 13-15 present investment style allocations for dominant portfolios selected on Cyclical versus non-Cyclical assets and Strategic versus non-Strategic assets respectively. In each figure, the first row corresponds to aggregate portfolio returns that have been calculated in each country-period grid as an equally-weighted average of annualised returns of the transactions falling in that grid, the second row corresponds to portfolios based on market value-weighted returns and the third row corresponds to portfolios based on transaction value-weighted returns. Similarly, the columns of graphs correspond to the selected time periods. Our first inspection of Table 6 reveals that all investment styles matter and their weights typically vary from 15% to 70%, they tend to rotate over time where a different dominant style appears in each time period and

Table 6. Posterior Moments of Investment Style Weights

			Posterior	DL	SZ	VL	GR	DL	SZ	VL	GR	DL	SZ	VL	GR	DL	SZ	VL	GR
Cyclical vs. Non-Cyclical				1985-1994				1995-1998				1999-2003				2004-2012			
	Equally Weighted	FSD	Mean	0.09	0.11	0.10	0.71	-	-	-	-	0.22	0.13	0.04	0.61	0.24	0.50	0.12	0.13
			Std. Dev.	0.07	0.11	0.10	0.19	-	-	-	-	0.12	0.09	0.03	0.10	0.08	0.13	0.10	0.03
		SSD	Mean	0.09	0.11	0.10	0.70	0.51	0.19	0.10	0.19	0.22	0.13	0.04	0.61	0.24	0.49	0.12	0.14
			Std. Dev.	0.08	0.09	0.09	0.16	0.21	0.15	0.09	0.14	0.12	0.09	0.03	0.10	0.08	0.13	0.10	0.03
	Market Value Weighted	FSD	Mean	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
			Std. Dev.	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
		SSD	Mean	-	-	-	-	-	-	-	-	0.20	0.28	0.22	0.30	-	-	-	-
			Std. Dev.	-	-	-	-	-	-	-	-	0.06	0.14	0.15	0.19	-	-	-	-
	Transaction Value Weighted	FSD	Mean	0.19	0.21	0.18	0.42	0.27	0.18	0.25	0.30	0.24	0.26	0.24	0.25	-	-	-	-
			Std. Dev.	0.14	0.17	0.15	0.21	0.17	0.11	0.15	0.18	0.18	0.19	0.18	0.19	-	-	-	-
		SSD	Mean	0.18	0.21	0.18	0.42	0.24	0.26	0.21	0.29	0.25	0.26	0.24	0.25	-	-	-	-
			Std. Dev.	0.14	0.16	0.16	0.21	0.19	0.21	0.17	0.18	0.19	0.19	0.18	0.19	-	-	-	-
Strategic vs. Non-Strategic				1985-1995				1996-1998				1999-2003				2004-2012			
	Equally Weighted	FSD	Mean	0.12	0.19	0.11	0.58	-	-	-	-	0.38	0.18	0.04	0.40	0.26	0.42	0.12	0.20
			Std. Dev.	0.08	0.12	0.10	0.13	-	-	-	-	0.18	0.13	0.04	0.13	0.09	0.13	0.10	0.03
		SSD	Mean	0.11	0.20	0.11	0.58	-	-	-	-	0.38	0.19	0.04	0.38	0.27	0.41	0.12	0.20
			Std. Dev.	0.07	0.12	0.10	0.13	-	-	-	-	0.18	0.13	0.04	0.13	0.09	0.13	0.10	0.03
	Market Value Weighted	FSD	Mean	-	-	-	-	-	-	-	-	0.29	0.31	0.21	0.20	-	-	-	-
			Std. Dev.	-	-	-	-	-	-	-	-	0.20	0.23	0.18	0.17	-	-	-	-
		SSD	Mean	-	-	-	-	-	-	-	-	0.32	0.28	0.19	0.21	-	-	-	-
			Std. Dev.	-	-	-	-	-	-	-	-	0.21	0.20	0.16	0.16	-	-	-	-
	Transaction Value Weighted	FSD	Mean	0.13	0.11	0.27	0.49	0.23	0.19	0.21	0.36	0.21	0.20	0.19	0.40	-	-	-	-
			Std. Dev.	0.09	0.15	0.20	0.29	0.17	0.16	0.18	0.23	0.18	0.17	0.16	0.23	-	-	-	-
		SSD	Mean	0.23	0.27	0.26	0.24	0.18	0.22	0.25	0.35	0.23	0.24	0.23	0.30	-	-	-	-
			Std. Dev.	0.16	0.19	0.18	0.17	0.16	0.17	0.16	0.22	0.20	0.16	0.19	0.20	-	-	-	-

Note: Table 6 presents the first two posterior moments of investment style weight coefficients for the average efficient portfolios. FSD denotes first-degree stochastic dominance, SSD denotes second-degree stochastic dominance, DL, SZ, VL, and GR denote debt-leverage, size, value and growth styles respectively in some cases for different return definition, while style allocations of FSD and SSD portfolios are in agreement. It is striking that Growth appears more frequently as the dominant investment style, while Value appears as the least important always accounting for 5% to 15% of portfolio return, a result which appears in contrast with the typical international evidence on equity portfolios, see Rau (2012). Figures 10-12 and 13-15 suggest that investment styles in general tend to exhibit relatively stable patterns across efficient portfolios, among which portfolio allocations for equally-weighted privatization returns tend to exhibit the most clear and stable style profile.

In more detail, for Cyclical vs. non-Cyclical portfolio allocations, and equally-weighted privatization portfolios which signify that the investor is equally exposed to each transaction of the respective country-period grid, we observe that investment styles tend to rotate across periods, where Growth accounts for 70% of portfolio return in the period 1985-1994, Debt-Leverage accounts for 50% in the period 1995-1998, Growth reverts in the subsequent period of 1999-2003 accounting for 60% and finally Size accounts for 50% in the last period of 2004-2012. Recall that in periods covering a full business cycle or a recession, such as 1985-1994 and 1999-2003, both FSD and SSD overweight non-Cyclical assets, of which growth characteristics tend to capture more than 60% of the selected portfolio return. It is striking that the investment style profile remains stable for the full set of efficient FSD and SSD portfolios in 1999-2003 despite the weight reversal on Cyclical versus non-Cyclical funds, thus allowing growth characteristics to support the evolution of portfolio composition. There are two notable exceptions: first, the expansion period 1995-1998 in which the FSD allocation overweights Cyclical assets which are shown to exhibit a significant Debt Leverage investment style and second, the full cycle period 2004-2012 in which both FSD and SSD overweight non-Cyclical assets which exhibit Size investment style, the latter also supported by the absence of FSD and SSD portfolios when country fund returns are defined as market value- and transaction value-weighted returns. The high relevance of Size during this period - which includes the global credit crisis - is consistent with the findings of Perez-Quiros and Timmermann (2000) that attribute the high required investor premium to the asymmetric impact of collateral damage on small companies. Growth reappears in the same periods consistently, for portfolios based on market value-weighted returns, but in a much smaller scale where the rest three styles also play an upgraded role. Finally, for portfolios based on transaction value-weighted returns, we observe a strong presence of Growth style in the first full cycle period 1985-1994, which evolves into a more balanced investment style during the next cycle 1995-2003 and the market benchmark during the third cycle 2004-2012.

Turning our attention to Strategic vs. non-Strategic allocations, we observe that portfolios based on equally-weighted privatization returns are characterised primarily by Growth investment style in the full cycle period 1985-1995, jointly by Growth and Debt Leverage in the recession period 1999-2003 and jointly by Debt Leverage and Size in the last full cycle period 2004-2012. Recall that both FSD and SSD overweight non-Strategic funds except of the last period in which characteristics other than Growth dominate, particularly Size and Debt Leverage. In the two remaining cases of allocations on funds based on market value- and transaction value-weighted returns, we observe a much more balanced investment style profile in all periods with available FSD and SSD portfolios, which overweight non-Strategic assets, with one notable exception. In particular, recall that for allocations of funds based on transaction value-weighted returns in the full cycle period 1985-1995, FSD and SSD are in disagreement. SSD portfolios stably overweight Strategic assets, while FSD portfolios agree with SSD for high levels of efficiency and then exhibit a reversal overweighting non-Strategic assets. This picture is also reflected in the investment style allocation characteristics, where SSD portfolios show a rather balanced and stable profile, while FSD portfolios are characterised primarily by Growth style which is diminished as asset allocation transits to non-Strategic asset overweighting and lower efficiency.

Overall our evidence suggests that, in contrast with the international evidence for conventional equity portfolios, Growth style plays a protagonist role in driving the return of both FSD and SSD portfolios from 1985 to 1994, while Size tends to lead portfolio returns from 2004 to 2012, the latter being in agreement with the international evidence for conventional equity portfolios, see Perez-Quiros and Timmermann (2000). Finally, Growth and a smaller but balanced participation of the remaining styles are found to lead returns from 1995 to 2003. In contrast with the evidence on conventional equity portfolios, see Rau (2012), our results show that Value is the least important style in all periods.

4 Concluding Remarks

In this paper we contribute an interdisciplinary approach to examine the robustness of portfolio optimality and performance attribution empirically, with applications to a unique global data set on privatized state assets. Given the major impact of privatization policies globally, this paper is motivated by the lack of evidence on the behaviour of privatized assets from a portfolio perspective and the resulting poor contribution to government privatization planning and active asset management.

Thus we consider the global privatization portfolio of exchange-traded assets from 1985 to 2012 in the context of first- and second-degree stochastic dominance efficiency (FSD, SSD). For a buy-and-hold strategy of a global asset manager, we employ optimization procedures proposed by Scailett and Topaloglou (2010) to estimate all possible portfolios in the context of Strategic vs non-Strategic and Cyclical vs non-Cyclical asset allocations that dominate the benchmark portfolio and provide a complete efficiency ranking in sequential sub-periods covering full or part of the business cycle and for different definitions of country fund returns. Our evidence reveals a significant number of portfolios which first- and second-degree stochastically dominate the market benchmark. For asset allocations on Cyclical vs. Non-Cyclical country funds we identify both FSD and SSD dominant portfolios which are shown to overweight Non-Cyclical assets in most cases. Moreover, for asset allocations on Strategic vs. Non-Strategic assets we also identify both FSD and SSD dominant portfolios which are now shown to overweight Non-Strategic assets in most cases. For the majority of cases, the sequence of efficiency-ranked dominant portfolios is shown to be smooth and stable, while in a significant number of cases FSD and SSD allocations tend to agree. For equally-weighted returns, where within each country fund the exposure to each individual privatization transaction is the same, our evidence reveals the existence of both FSD and SSD portfolios in all periods for Cyclical vs. Non-Cyclical allocations. However, this is not the case for market value-weighted and transaction value-weighted returns, which exhibit size characteristics which interfere with the business cycle. The above picture is weakened for Strategic vs. Non-Strategic allocations. In our view, the observed rotation of portfolio weights across business cycles reflects the superior performance of small size companies and large privatization transactions signalling less state control.

Given our asset allocation results, we proceed to portfolio return attribution analysis using robust Bayesian procedures along the lines of Kloek and van Dijk (1978) and van Dijk and Kloek (1980) in the context of Sharpe (1992) style asset management. We construct factor mimicking portfolios to proxy the latent investment styles of Debt-Leverage, Size, Value and Growth. Our evidence suggests that Growth style tends to drive more frequently the return of both FSD and SSD portfolios during the first business cycle in our sample, from 1985 to 1994, which in contrast with the international evidence for conventional equity portfolios. Moreover, Size style tends to drive portfolio returns during the last business cycle, from 2004 to 2012, a result in agreement with the international evidence for conventional equity portfolios. We identify primarily Growth and a balanced participation of the remaining styles driving returns during the cycle from 1995 to 2003. Finally, our evidence suggests that Value appears as the least influencing style in all periods, a result also in contrast with the broader international evidence on conventional equity portfolios but consistent with recent findings of Fama and French (2015).

We have employed for the first time SD methodologies to uncover optimal portfolio selection and asset management style properties, irrespective of investor preferences, for the global privatization portfolio of listed assets from 1985 to 2012, covering approximately three business cycles. To the best of our knowledge this is the first comprehensive analysis of this scale for privatization assets. We believe it provides useful evidence for portfolio investment as well as policy analysis.

References

Alexander G.J., and A.M. Baptista (2004), A comparison of VaR and CVaR constraints on portfolio selection with the mean-variance model, Management Science, 50(9), 1261-1273

Anderson, G., (1996), Nonparametric Tests of Stochastic Dominance in Income Distributions, Econometrica, 64, 1183-1193.

Atanasov V, (2005), How much value can blockholders tunnel? Evidence from the Bulgarian mass privatization auctions, Journal of Financial Economics, 76, 1, 191-234

Barberis, N., and A. Shleifer, (2003), Style Investing, Journal of Financial Economics, 68, 161–199

Barrett, G., and S. Donald, (2003), Consistent Tests for Stochastic Dominance, Econometrica, 71, 71-104.

Bawa, V., (1975), Optimal Rules for Ordering Uncertain Prospects. Journal of Financial Economics, 2, 95-121.

Beach, C., and R. Davidson, (1983), Distribution-free Statistical Inference with Lorenz Curves and Income Shares, Review of Economic Studies, 50, 723-735.

Borisova G and A Cowan, (2012), The Other Side of Privatization: Acquirer Performance, Working Paper, Iowa State University

Bortolotti, B., M. Fantini, and D. Siniscalco, (2003), Privatization around the World: Evidence from Panel Data, Journal of Public Economics, 88, 305-332

Boycko, M., A. Shleifer and R. W. Vishny, (1996), A Theory of Privatisation, Economic Journal, 106, 435, 309-319

Boyer, H. B., (2011), Style-Related Comovement: fundamentals or labels?, Journal of Finance, 66, 307–332

Brown, S. and W. Goetzmann, (1997), Mutual Fund Styles, Journal of Financial Economics, 43, 373-399

Cochrane J H, (2005), The risk and return of venture capital, Journal of Financial Economics, 75, 3-52

Czerny A, Höffler F and Se-il Mun, (2014), Hub port competition and welfare effects of strategic privatization, Economics of Transportation, 3, 211–220

Davidson, R., and J.-Y. Duclos, (2000), Statistical Inference for Stochastic Dominance and for the Measurement of Poverty and Inequality, Econometrica, 68, 1435-1464.

Dentcheva D. and A. Ruszczynski, (2010), Robust stochastic dominance and its application to risk-averse optimization, Mathematical Programming A, 123(1), 85-100

Dewenter K and P H Malatesta, (1997), Public Offerings of State-Owned And Privately-Owned Enterprises: An International Comparison, Journal of Finance, 52, 4, 1659-1679

Dupacova J. and M. Kopa, (2012), Robustness in stochastic programs with risk constraints, Annals of Operations Research, 200 (1), 55-74.

Dyck A and L Zingales, (2004), Private Benefits of Control: An International Comparison, Journal of Finance, 59, 2, 537-600

Fabian C., G. Mitra, and D. Roman, (2011), Processing second-order stochastic dominance models using cutting-plane representations, Mathematical Programming, A 130(1), 33-57

Faccio, M., (2006), Politically Connected Firms, American Economic Review, 96, 1, 369-386

Fama,E. and K. French, (1992), The Cross Section of Expected Stock Returns, Journal of Finance, 47, 427–465

Fama,E. and K. French, (1993), Common Risk Factors in the Returns on Stocks and Bonds, Journal of Financial Economics, 33, 3–56

Fama,E. and K. French, (2015), A five-factor asset pricing model, Journal of Financial Economics, 116 (1), 1–22

M. Frittelli and E. Rosazza Gianin, (2002), Putting order in risk measures. Journal of Banking and Finance, 26(7):1473–1486

Hadar, J., Russell, W.R., (1969), Rules for ordering uncertain prospects. American Economic Review, 59, 25–34.

Hanoch, G., Levy, H., (1969), The efficiency analysis of choices involving risk. Review of Economic Studies, 36, 335–346.

J.P.Morgan, (2012), Regime Change: Implications of macro shifts on asset class and portfolio performance, J.P.Morgan Asset Management, Research Report

Judge, G. G., W. E. Griffiths, R. Carter Hill, H. Lütkepohl and T-C Lee, (1985), The Theory and Practice of Econometrics, Wiley Series in Probability and Statistics, 2nd edition

Keim, D. and A. Madhavan, (1997), Transactions costs and investment style: an inter-exchange analysis of institutional equity trades, Journal of Financial Economics, 46, 265-292

Kloek, T. and Van Dijk, H.K., (1978), Bayesian Estimates of Equation System Parameters: an Application of Integration by Monte Carlo, Econometrica, 46(1), 1-19.

Kose B, C Otrok and E Arprasad, (2012), Global Business Cycles: Convergence or Decoupling?, International Economic Review, 53, 2, 511-538

Kuosmanen, T., (2004), Efficient Diversification According to Stochastic Domi- nance Criteria. Management Science, 50, 1390-1406.

Lebovitz D, Dwyer A and Manley J, (2016), Cyclicals vs. defensives: The valuation imbalance, J. P. Morgan Market Bulletin, July

Leshno, Moshe and Haim Levy, (2002), Preferred by "All" and Preferred by "Most" Decision Makers: Almost Stochastic Dominance, Management Science, 48, 8, 1074-1085

Levy, H., Hanoch, G., (1970), Relative effectiveness of efficiency criteria for portfolio selection. Journal of Financial and Quantitative Analysis, 5, 63–76.

Levy, H., (1992), Stochastic dominance and expected utility: Survey and Analysis, Management Science, 38(4), 555-593.

Linton, O., E. Maasoumi and Y.-J. Whang, (2005), Consistent testing for stochastic dominance under general sampling schemes, Review of Economic Studies, 72, 735-765.

Li K, T Wang, Y-L Cheung and P , (2011), Privatization and Risk Sharing: Evidence from the Split Share Structure Reform in China, Review of Financial Studies, 24, 7, 2499-2525

Liu Y., and H. Hu, (2013), Stability analysis of stochastic programs with second order dominance constraints, Mathematical Programming A 142(1-2), 435-460

Lizyayev, Andrey and Andrzej Ruszczynski, (2012), Tractable Almost Stochastic Dominance, European Journal of Operational Research, 218, 448–455

Lozano S., and E. Gutierrez, (2008), Data envelopment analysis of mutual funds based on second-order stochastic dominance, European Journal of Operations Research, 189(1), 230-244.

Lizyayev A., and A. Ruszczynski, (2012), Tractable almost stochastic dominance, European Journal of Operations Research, 218(2), 448-455.

Markowitz, H. M, (1952), The utility of wealth, Journal of Political Economy, 60, 151-156

Massa, M. and L. Zhang, (2009), Cosmetic mergers: The effect of style investing on the market for corporate control, Journal of Financial Economics, 93, 400-427

Megginson W, R C Nash, J M Netter and Schwartz, (2000), The Long-Run Return to Investors in Share Issue Privatization, Financial Management, 29, 1, 67-77

Morningstar, (2011), Morningstar Global Equity Classification Structure, Morningstar Research, May

Mukherjee and K Suetrong, (2009), Privatization, strategic foreign direct investment and host-country welfare, European Economic Review, 53, 7, 775-785

OECD, (2010), Privatisation in the 21st Century: Summary of Recent Experiences, Best Practice Report, OECD Working Group on Privatisation and Corporate Governance of State Owned Assets, Paris

Perez-Quiros G and A Timmermann, (2000), Firm Size and Cyclical Variations in Stock Returns, Journal of Finance, LV, 3, 1229-1262

Post, T., (2003). Empirical Tests for Stochastic Dominance Efficiency. Journal of Finance 58, 1905-1031.

Post, T. and M. Kopa, (2013), General linear formulations of stochastic dominance criteria, European Journal of Operational Research, 230, 321–332

Quirk, J.P. and R. Saposnik, (1962), Admissibility and Measurable Utility Function, Review of Economic Studies, 29, 140-146.

Rau R, (2012), Investment Styles and their Performance in Different Market Cycles, Deutsche Asset and Wealth Management, White Paper

Scaillet, O. and N. Topaloglou, (2010), Testing for Stochastic Dominance Efficiency, Journal of Business and Economic Statistics, 28, 169-180

Sharpe, W.F., (1988), Determining the Fund's Effective Asset Mix, Investment Management Review, November-December, 59-69.

Sharpe, W.F., (1992), Asset Allocation: Management Style and Performance Measurement, Journal of Portfolio Management, vol. 18, 7-19.

Shleifer, A., (1998), State versus Private Ownership, Journal of Economic Perspectives, 12, 4, 133-150

Shleifer, A. and R. W. Vishny, (1994), Politicians and Firms, Quarterly Journal of Economics, 109, 4, 995-1025

Spiess D K and J Aflek-Graves, (1995), Underperformance in long-run stock returns following seasoned equity offerings. Journal of Financial Economics, 38, 243-267

Teo, M. and Woo, SJ., (2004), Style Effects in the Cross-Section of Stock Returns, Journal of Financial Economics, 74, 367-398

Tzeng, Larry Y., Rachel J. Huang and Pai-Ta Shih (2013), Revisiting Almost Second-Degree Stochastic Dominance, Management Science, 59(5), 1250-1254

Van Dijk, H.K. and Kloek, T., (1980), Further Experience in Bayesian Analysis Using Monte Carlo Integration, Journal of Econometrics, vol. 14, 307-328.

Wahal S. and M. Deniz Yavuz, (2013), Style Investing, Comovement and Return Predictability, Journal of Financial Economics, 107(1), 136-154.

Wei Z, O Varela, J D'Souza and M K Hassan, (2003), The Financial and Operating Performance of China's Newly Privatized Firms, Financial Management, 32, 2, 107-126

Wei Z, F Xie, and S Zhang, (2005), Ownership Structure and Firm Value in China's Privatized Firms: 1991-2001, Journal of Financial and Quantitative Analysis, 40, 1, 87-108

Xu, Guoa, Xuehu Zhua, Wing-Keung Wongb and Lixing Zhua, (2013), A note on almost stochastic dominance, Economics Letters, 121, 252–256

Yamazaki, H. and H. Konno, (1991), Mean Absolute Deviation Portfolio Optimization Model and its Application to Tokyo Stock Market, Management Science, 37, 519-531

Young, M., (1998). A minimax portfolio selection rule with linear programming solution. Management Science, 44(5), 673-683.

Appendix

Figure 3.1

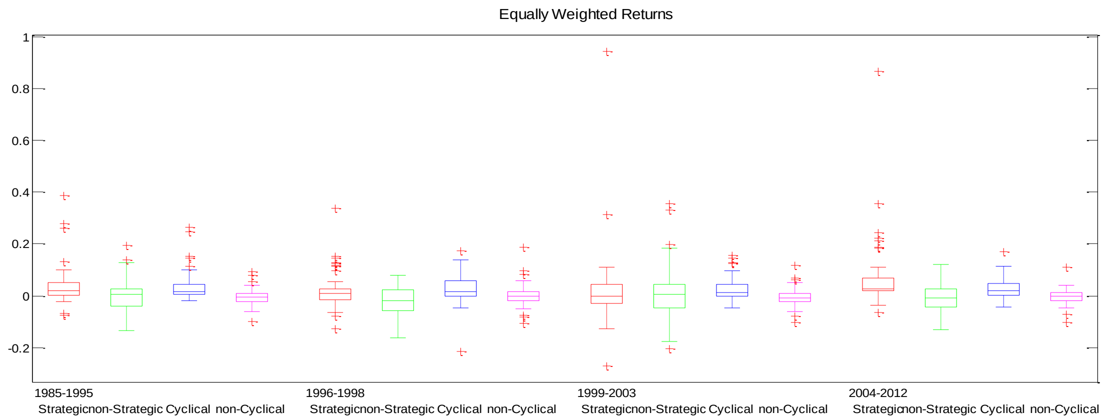


Figure 3.2

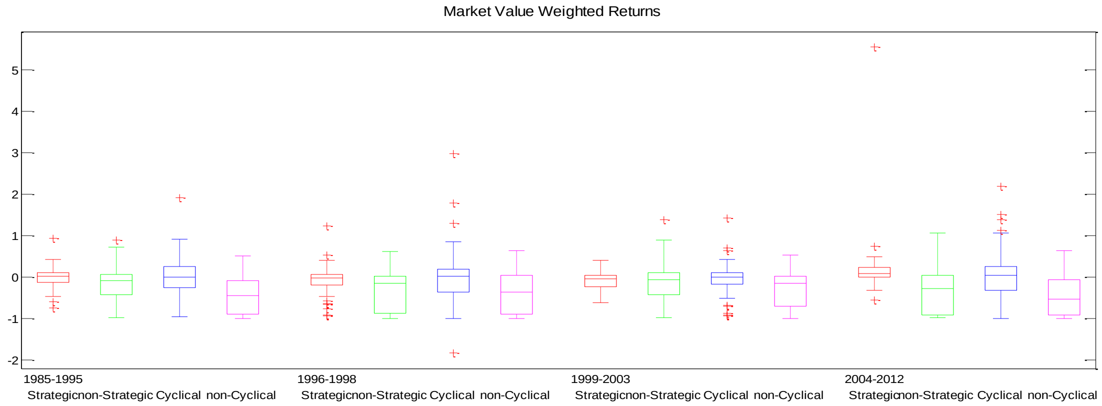


Figure 3.3

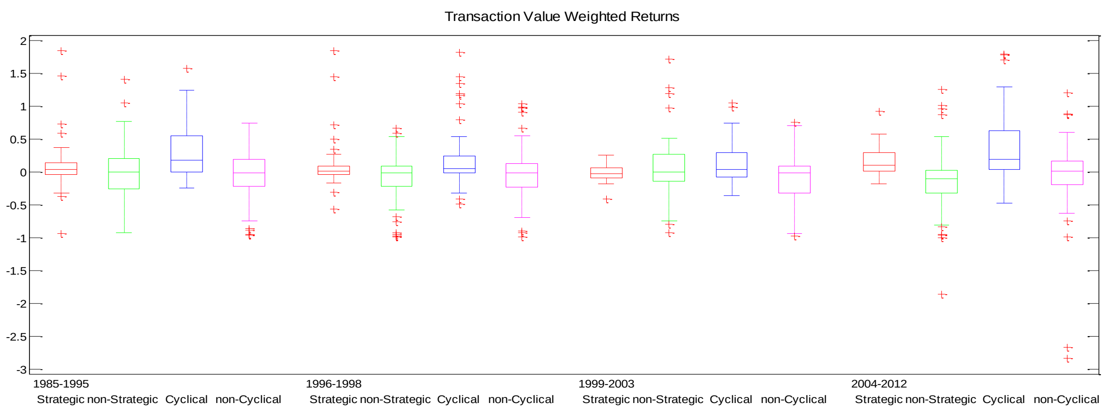
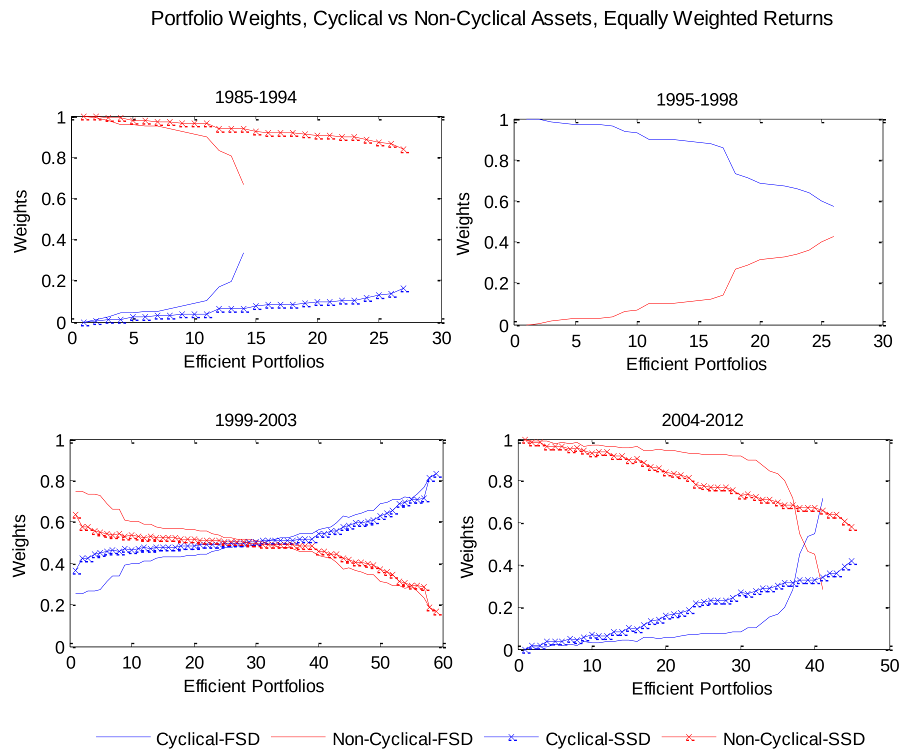
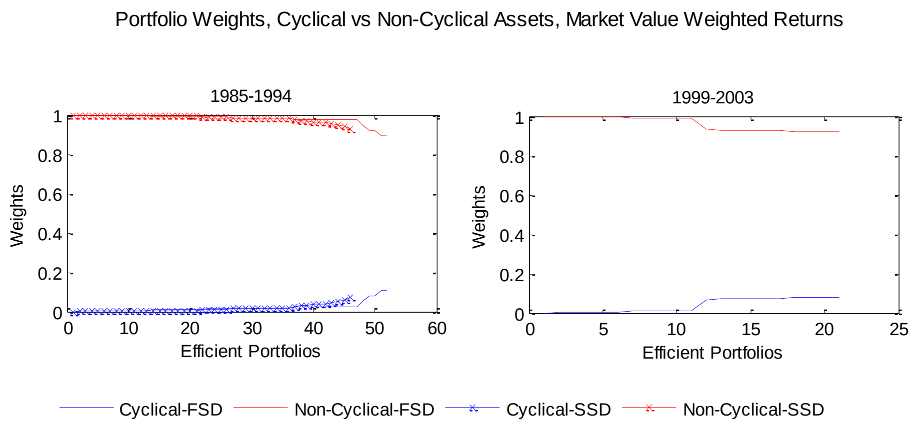


Figure 4



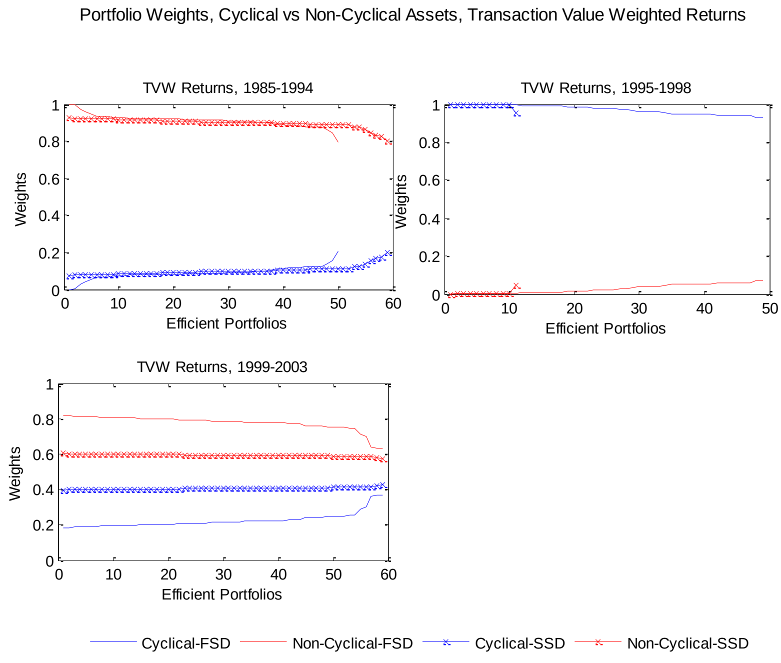
Note: Figure 4 presents investment weights for all the efficient portfolios ordered from best to worst. FSD denotes first-degree stochastic dominance, SSD denotes second-degree stochastic dominance.

Figure 5



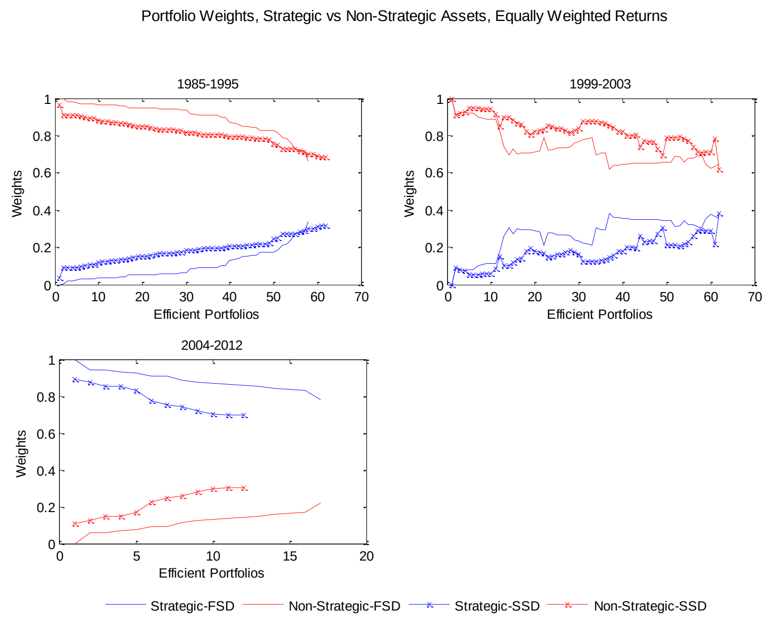
Note: Figure 5 presents investment weights for all the efficient portfolios ordered from best to worst. FSD denotes first-degree stochastic dominance, SSD denotes second-degree stochastic dominance

Figure 6



Note: Figure 6 presents investment weights for all the efficient portfolios ordered from best to worst. FSD denotes first-degree stochastic dominance, SSD denotes second-degree stochastic dominance

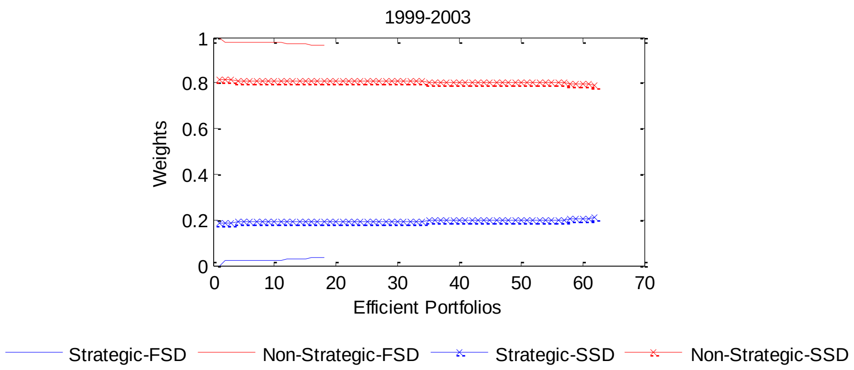
Figure 7



Note: Figure 7 presents investment weights for all the efficient portfolios ordered from best to worst. FSD denotes first-degree stochastic dominance, SSD denotes second-degree stochastic dominance.

Figure 8

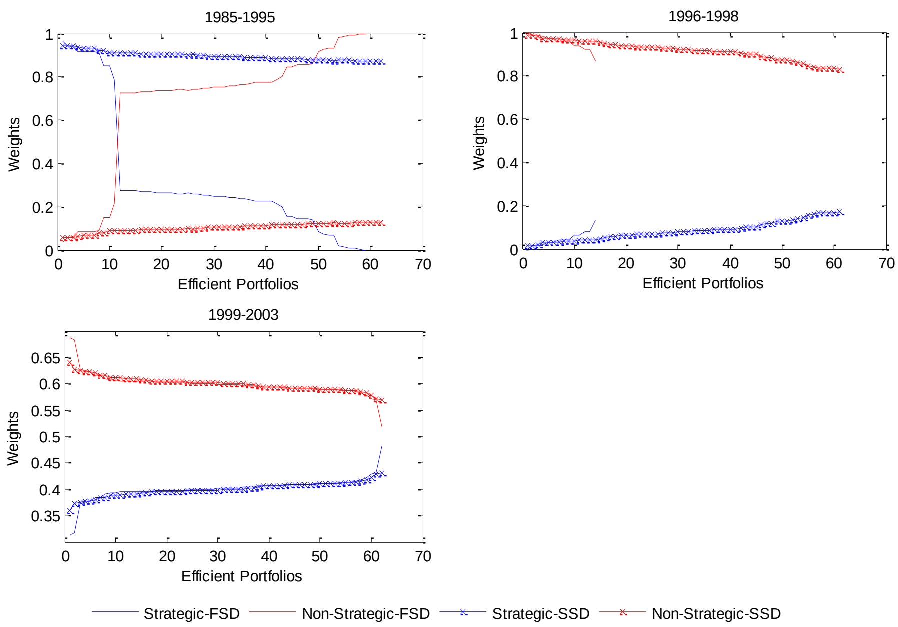
Portfolio Weights, Strategic vs Non-Strategic Assets, Market Value Weighted Returns



Note: Figure 8 presents investment weights for all the efficient portfolios ordered from best to worst. FSD denotes first-degree stochastic dominance, SSD denotes second-degree stochastic dominance.

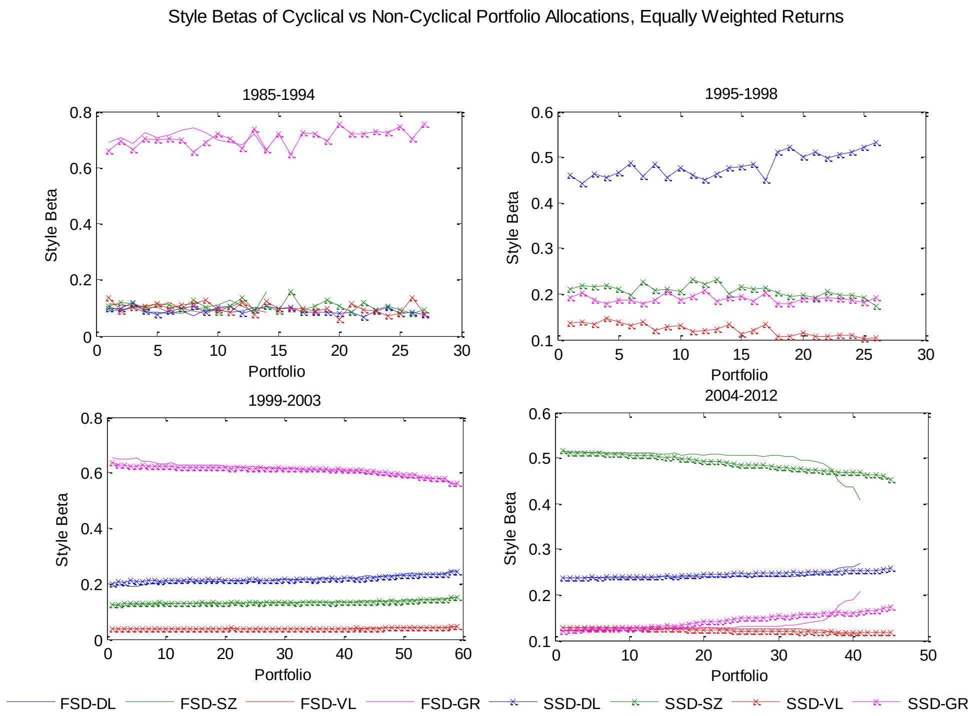
Figure 9

Portfolio Weights, Strategic vs Non-Strategic Assets, Transaction Value Weighted Returns



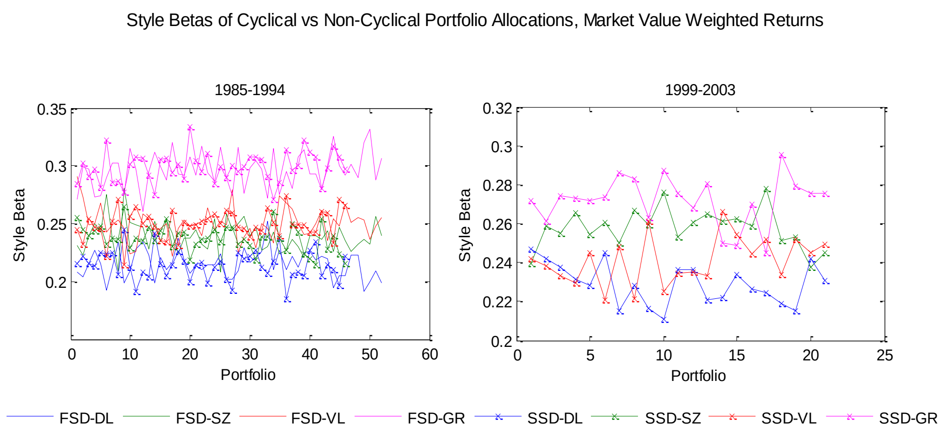
Note: Figure 9 presents investment weights for all the efficient portfolios ordered from best to worst. FSD denotes first-degree stochastic dominance, SSD denotes second-degree stochastic dominance.

Figure 10



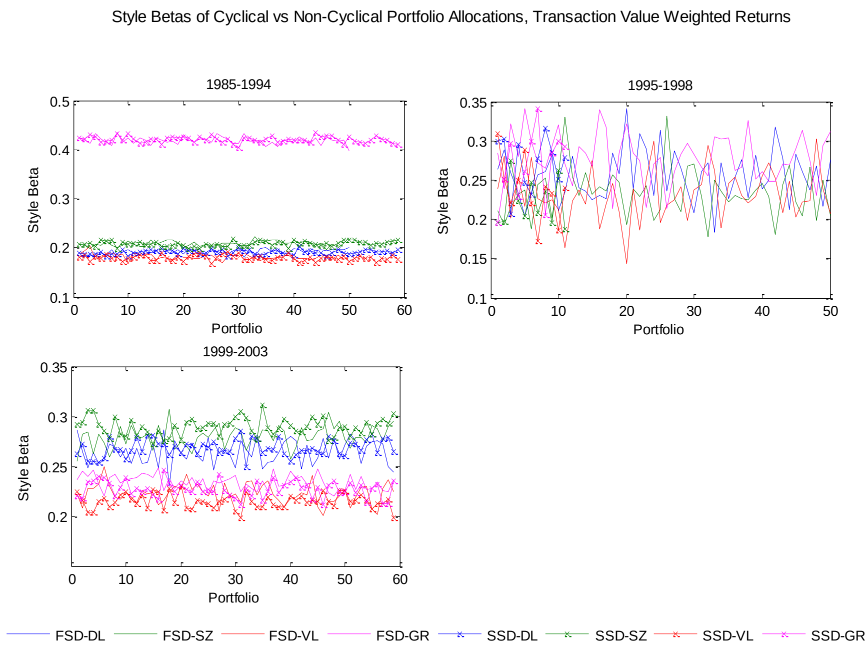
Note: Figure 10 presents investment style beta coefficient for all the efficient portfolios ordered from best to worst. FSD denotes first-degree stochastic dominance, SSD denotes second-degree stochastic dominance, DL, SZ, VL, and GR denote debt-leverage, size, value and growth styles respectively.

Figure 11



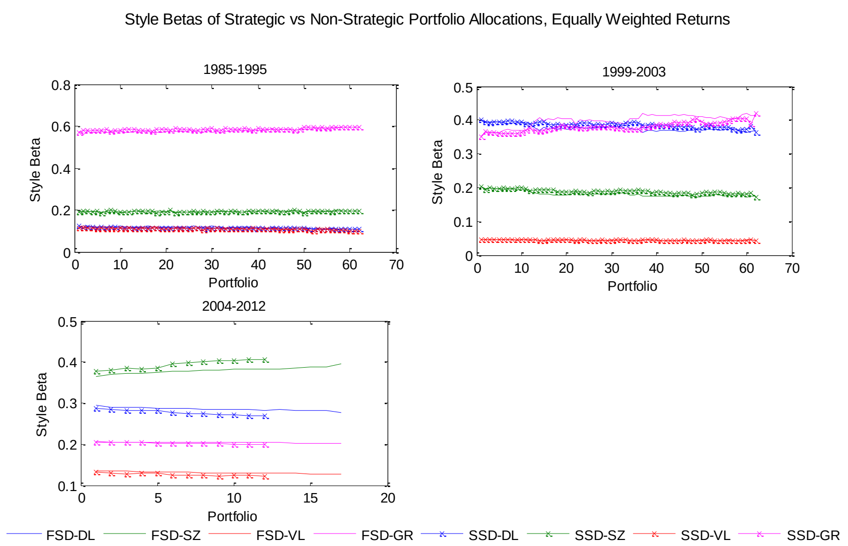
Note: Figure 11 presents investment style beta coefficient for all the efficient portfolios ordered from best to worst. FSD denotes first-degree stochastic dominance, SSD denotes second-degree stochastic dominance, DL, SZ, VL, and GR denote debt-leverage, size, value and growth styles respectively.

Figure 12



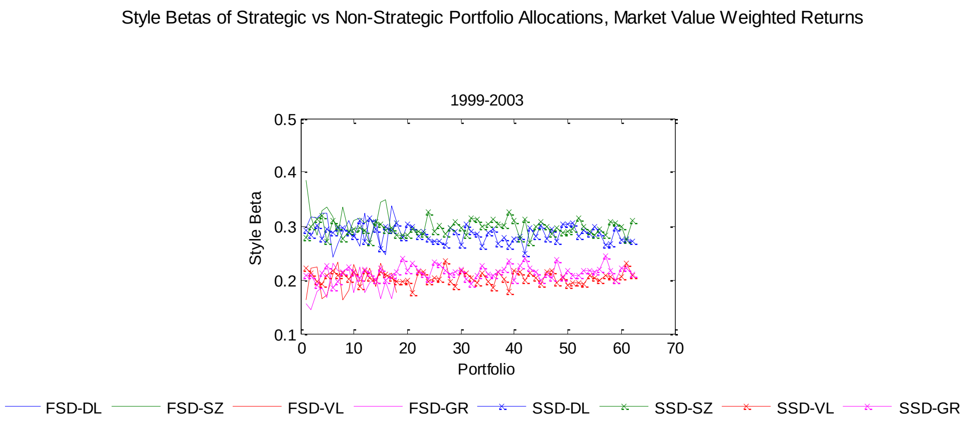
Note: Figure 12 presents investment style beta coefficient for all the efficient portfolios ordered from best to worst. FSD denotes first-degree stochastic dominance, SSD denotes second-degree stochastic dominance, DL, SZ, VL, and GR denote debt-leverage, size, value and growth styles respectively.

Figure 13



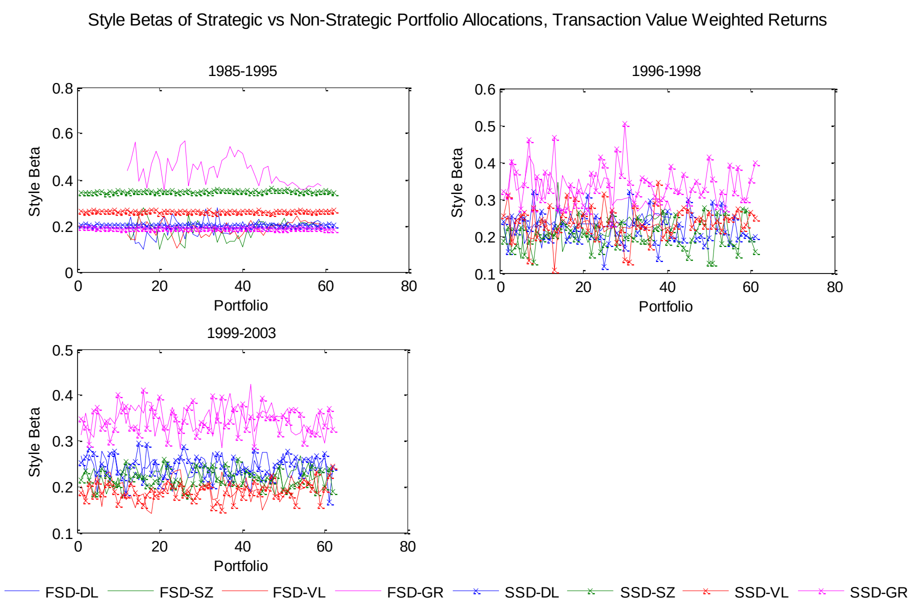
Note: Figure 13 presents investment style beta coefficient for all the efficient portfolios ordered from best to worst. FSD denotes first-degree stochastic dominance, SSD denotes second-degree stochastic dominance, DL, SZ, VL, and GR denote debt-leverage, size, value and growth styles respectively.

Figure 14



Note: Figure 14 presents investment style beta coefficient for all the efficient portfolios ordered from best to worst. FSD denotes first-degree stochastic dominance, SSD denotes second-degree stochastic dominance, DL, SZ, VL, and GR denote debt-leverage, size, value and growth styles respectively.

Figure 15



Note: Figure 15 presents investment style beta coefficient for all the efficient portfolios ordered from best to worst. FSD denotes first-degree stochastic dominance, SSD denotes second-degree stochastic dominance, DL, SZ, VL, and GR denote debt-leverage, size, value and growth styles respectively.