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Charles Chevalier

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**THÈSE DE DOCTORAT**

**DE L'UNIVERSITÉ PSL**

Préparée à l'Université Paris-Dauphine

**Trois essais sur les stratégies de suivi de tendance**

Soutenue par

**Charles Chevalier**

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# Résumé

Les stratégies de suivi de tendance ont rencontré ces dernières années un fort d'intérêt de la part des investisseurs institutionnels. Leur bonne performance lors de la crise économique et financière de 2008 n'y est pas étrangère. Les années 2016 à 2018 ont rebattu les cartes, avec des performances jugées mauvaises par de nombreux clients. Cette thèse s'intéresse aux différentes caractéristiques des stratégies de suivi de tendance que sont la performance, le risque et les coûts d'exécution, et propose de nouvelles manières d'aborder ces sujets. Le chapitre 1 explique la différence de performance entre les styles de hedge funds en développant une famille hiérarchique de facteurs de tendance. Nos résultats confirment la présence de tendances au sein des stratégies CTA et Global Macro et montrent le caractère assurantiel de cette stratégie au sein de fonds issus de tous les styles de hedge funds. Le chapitre 2 propose une nouvelle décomposition du risque associée aux stratégies de suivi de tendance en une composante commune et une composante spécifique. L'extraction d'un facteur de risque systématique et son ajout aux modèles factoriels standards permettent de mieux expliquer les performances des hedge funds, et ce de manière différente du chapitre 1. Ces travaux ouvrent la voie à la construction d'indices de suivi de tendance. Enfin, le chapitre 3 aborde la question de l'exécution d'une stratégie de suivi de tendance. Le coût payé par l'investisseur, c'est-à-dire le coût associé à la gestion du portefeuille, n'est pas seulement fonction de la liquidité individuelle des actifs traités, mesurée par le coût d'exécution de chaque transaction. Ce coût total dépend également



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des décisions d'allocation prises par le gérant pour satisfaire aux objectifs de performance et de risque du fonds.

**Mots clés : suivi de tendance, fonds d'investissement, construction de portefeuille, liquidité**

# Abstract

Trend-following strategies became increasingly popular among institutional investors after exhibiting good performances during the 2008 global financial crisis. The 2016-2018 years reshuffled the cards due to disappointing performances. This thesis focuses on the different characteristics of the performances of trend following strategies, namely performance, risk and execution, and proposes new ways of analyzing them. Chapter 1 explains the differences in performance across hedge fund styles by developing a hierarchical set of time-series momentum factors. It confirms trends are harvested among CTA and Macro strategies, and suggests an exposure to trend is similar to an insurance. Indeed, individual funds are facing a tradeoff between the premium paid and the drawdown reduction. Chapter 2 proposes a break risk decomposition adapted to trend following strategies into systematic and specific components. The extracted systematic risk factor helps understanding hedge fund styles that were not exposed to the chapter 1 factor. This chapter paves the way for the construction of smart trend indices. Finally, Chapter 3 discusses the cost of implementing such strategies. The cost paid by the investor, which is the total implementation cost of the portfolio, is not only a function of the individual liquidity of traded assets, as measured by the trade-by-trade execution cost. This total cost is also the result of allocations decisions taken by the manager to satisfy the fund performance and risk objectives.

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**Key words : trend following, hedge funds, portfolio construction,  
liquidity**

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# Introduction générale

Cette introduction est rédigée autour des grandes questions posées par l'activité d'intermédiation entre épargnants et entreprises. Le sujet est abordé d'abord de manière générale, en précisant les interactions économiques entre ces agents, puis spécifiquement dans le cadre des fonds d'investissement alternatifs. Enfin, le cas particulier des fonds adoptant des stratégies de suivi de tendance est analysé.

## La gestion d'actifs

Tous les agents économiques font face à des choix. Dans le respect de leur contrainte budgétaire, les ménages décident soit d'épargner pour des projets futurs, soit de consommer la totalité de leur revenu disponible. Les entreprises font face à d'autres questions. Elles arbitrent entre des projets peu coûteux, peu risqués et à faible valeur ajoutée et des projets plus coûteux, plus risqués mais à forte valeur ajoutée. Elles ont alors des besoins de financement, d'autant plus importants qu'elles optent pour le second choix. L'ensemble de ces agents économiques se retrouvent sur différents marchés financiers, où l'offre vient des ménages et la demande des entreprises. Plusieurs intermédiaires participent à ces marchés à des niveaux différents. Les banques permettent la gestion des liquidités quotidiennes, transformées en crédits aux entreprises. Les assurances permettent le transfert de risque entre agents. Enfin, les gérants d'actifs permettent aux ménages d'investir l'argent dont ils

n'ont pas l'utilité immédiate. En tant qu'acteur sur ce marché, le gérant d'actifs a un double objectif. Côté entreprises, il assure une allocation optimale du capital, en sélectionnant et en finançant les projets créateurs de valeur. Côté épargnants, il crée des véhicules d'investissement adaptés à leurs besoins et contraintes. Le gérant d'actifs fournit alors aux épargnants deux services. D'une part, son expertise des marchés, symbolisée par sa maîtrise des actifs financiers lui donne l'opportunité de construire des portefeuilles équilibrés. D'autre part, sa capacité à mutualiser des risques au sein d'un véhicule d'investissement collectif permet aux épargnants d'accéder de manière efficace aux marchés financiers. Cette efficacité s'exprime à la fois par un univers d'investissement élargi et par un coût réduit. En pratique, il existe de nombreux types de fonds d'investissement et des niveaux de délégation de gestion variés, selon le degré de spécialisation des gérants d'actifs.

La diversité des actifs échangés sur les marchés financiers est grande. Les deux principaux marchés sont celui des actions, parts d'entreprises, et celui des obligations, instruments de dette. Actions et obligations peuvent avoir des caractéristiques très variables : secteur industriel, taille de l'entreprise, pays dans lequel celle-ci est installée, devise du pays. . . Elles permettent de mobiliser l'épargne des ménages dans le but de répondre aux besoins de financement des entreprises. D'autres actifs comme les taux d'intérêt court terme, les devises et les matières premières assurent des fonctions similaires mais sont échangés sur d'autres marchés. Tous ces marchés financiers sont difficilement accessibles en direct par les épargnants, du fait de la difficulté d'analyse des titres investissables et de leur multiplicité. Les ménages délèguent donc la gestion de leurs actifs à des spécialistes. En pratique, il existe plusieurs manières pour un investisseur d'avoir recours aux services d'un gestionnaire d'actifs. Les deux principales sont l'établissement d'un mandat de gestion et l'achat de parts de fonds ouverts. Un mandat de gestion est un contrat spécifique signé entre un investisseur et un gérant, fait sur mesure pour répondre aux

exigences particulières du premier. A l'inverse, un fonds ouvert est un organisme de placement collectif qui permet à plusieurs épargnants de confier leur argent à un gérant via l'achat de parts. Le gérant gère l'ensemble des actifs constituant le fonds de la même manière, via une stratégie prédéterminée et en accord avec l'ensemble des porteurs de parts. L'intérêt de la mutualisation est de réduire les coûts de gestion. Contrairement aux mandats, les fonds ouverts sont des produits standardisés. Ils représentent la grande majorité des sommes collectées par les gérants d'actifs. C'est pourquoi nous nous concentrerons sur ce type de véhicules par la suite.

Dans le contexte d'un fonds, le contrat de délégation que les épargnants signent avec les gestionnaires d'actifs s'apparente à un problème principal-agent mettant en jeu des forces opposées. Le principal, ici l'épargnant, vise à acquérir le plus d'information possible pour juger si le contrat est bien rempli. L'agent, ici le gérant d'actifs, cherche lui à ne pas divulguer toute l'information dont il dispose pour garder sa valeur ajoutée. Le risque majeur de cette situation d'agence est un mauvais fonctionnement de cette relation. Un équilibre de marché correspond à la situation où d'une part, les épargnants sélectionnent exactement le gérant qui leur correspond et au bon prix et d'autre part, les gérants d'actifs sont rémunérés justement, en fonction de la qualité de leur produit. Les épargnants, s'ils ne disposent pas de toute l'information nécessaire, ne peuvent pas sélectionner le bon gérant d'actifs et l'équilibre de marché ne peut être atteint. L'intérêt de tous est donc de réduire l'asymétrie d'information et de mettre en place un système alignant les intérêts des deux parties afin d'arriver à l'équilibre. Le fait de déléguer la gestion de ses actifs pose un certain nombre de questions liées à l'asymétrie d'information, que la recherche académique sur les investissements s'est appropriée.

Le premier moyen de réduire l'asymétrie d'information est de permettre

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à l'épargnant de mieux mesurer la performance d'un gérant. Il existe deux approches pour analyser et comprendre une stratégie d'investissement. La première exploite les positions en portefeuille. A partir de celles-ci, il est possible de décrypter quels sont les risques ou les convictions du gérant. Grinblatt et Titman (1989) [52] se fondent sur l'analyse de ces positions pour mesurer la capacité des gérants d'actifs à délivrer une performance ajustée du risque satisfaisante. Lorsque cette information n'est pas disponible, la seule solution consiste à analyser les rendements passés du fonds. Cette approche est plus complexe, mais par le jeu des relations entre les rendements du fonds et ceux d'autres actifs, il est possible d'inférer quel est le processus d'investissement d'un fonds donné et d'en comprendre ses risques. Une première approche univariée consiste à analyser les fonds mutuels sous l'angle rendement-risque (Sharpe, 1966) [92], via le ratio éponyme. Lo (2002) [74] propose une correction du ratio de Sharpe pour intégrer les potentielles autocorrélations présentes dans les rendements, qui ont pour conséquence la surestimation du ratio.

La performance peut se mesurer de manière absolue ou de manière relative, en comparant les performances du fonds à ses pairs. L'approche relative consiste à régresser les rendements de la stratégie analysée sur les rendements d'actifs de marché. Ces actifs de marché peuvent également être regroupés selon des caractéristiques communes pour former un facteur de risque explicatif, plus à même d'expliquer une stratégie. L'approche factorielle s'est d'abord développée dans le contexte des fonds investissant exclusivement sur les marchés actions, avec notamment le modèle de Fama et French (1992) [43] constitué de trois facteurs : marché, size et value. Cette méthode d'analyse de performance, formalisée par Sharpe (1992) [93], est appelée "returns-based style analysis". Elle permet notamment de comparer la performance toutes choses égales par ailleurs, c'est-à-dire en contrôlant par les risques pris par le gérant.

Les portefeuilles diversifiés ont la particularité d’investir sur plusieurs marchés, et pas uniquement sur celui des actions. Un modèle de risque comprenant uniquement des facteurs actions a dans ce contexte peu d’intérêt. En effet, un investissement en obligations gouvernementales ou d’entreprises, en devises, ou encore en matières premières, aura a priori des caractéristiques différentes d’un investissement en actions. L’extension naturelle de l’approche ”returns-based” à un portefeuille diversifié consiste alors simplement à ajouter des facteurs statiques, dits *buy-and-hold*, représentant les différentes classes d’actifs. C’est la première étape du modèle d’analyse de performance des fonds d’investissement diversifiés. Sharpe (1992) [93] propose un modèle de ce type en ajoutant différents indices obligataires aux facteurs classiques de valorisation des actions.

Au delà de la bonne mesure de la performance et de la qualité du gérant, le choix de l’investisseur est aussi facilité par une mesure de la persistance de ces performances. Grinblatt et Titman (1989) [53] analysent justement dans quelle mesure les performances passées d’un gérant d’actifs annoncent des performances futures. En supposant une asymétrie d’information nulle, l’épargnant accède complètement à l’information. Il a alors parfaitement connaissance de la qualité du gérant et de sa capacité à générer de la valeur. Il peut donc vendre les parts de fonds de faible qualité et investir dans les gérants de forte qualité, en fonction de ses préférences individuelles. En agrégeant cela à l’échelle du marché, l’équilibre peut désormais être atteint. Berk et Green (2004) [23] proposent un modèle économique reliant les flux d’investissement dans un fonds et la qualité de celui-ci, mesurée par ses performances.

Un autre moyen de contrôle est situé en amont du processus de gestion. Celui-ci n’est pas fonction des performances, mais vise plutôt à mesurer les intentions du gérant. En absence de valeur ajoutée claire, un autre moyen

pour les épargnants de sélectionner les gérants d'actifs est de filtrer ceux qui ont des potentiels conflits d'intérêt, de l'aléa moral ou tout autre mécanisme remettant en cause leur bon vouloir. Les compétences et la valeur ajoutée d'un gérant peuvent ainsi être mesurées par les épargnants. L'asymétrie d'information est réduite par cette approche, permettant aux épargnants de sélectionner les bons gérants.

Toutes ces questions d'évaluation des gérants d'actifs sont évidemment d'autant plus importantes que la transparence est faible et les stratégies mises en oeuvre sophistiquées.

## **Les fonds d'investissement alternatifs**

La gestion alternative désigne à la fois l'investissement en actifs non traditionnels, illiquides et complexes, une manière d'investir et un cadre juridique. Les classes d'actifs peu liquides tels que le capital-investissement, les infrastructures, l'immobilier, l'art, le vin sont considérés comme des investissements alternatifs, car non liés au système traditionnel de financement comme le sont les actions, les obligations et les devises. Ces actifs ne sont pas standards, ce qui rend la transmission d'information et la transparence entre le gérant et l'investisseur plus délicate. Le second pan de la gestion alternative, représentée par les hedge funds, se définit plutôt par la forme et les objectifs de l'investissement. La décorrélation recherchée est le résultat d'une approche spécifique des marchés traditionnels : utilisation de dérivés, de levier via des mécanismes d'emprunt, réallocation fréquente du portefeuille. Une autre différence entre gestion traditionnelle et alternative concerne la structuration des produits : les fonds alternatifs sont domiciliés dans des paradis fiscaux ou sur des plateformes offshore. Enfin, il existe des produits d'investissement qui sont au croisement de ces deux approches, c'est-à-dire un investissement dynamique, avec éventuellement un effet de levier, sur des

actifs alternatifs. Le besoin de mesurer la performance et les risques est d'autant plus critique que la complexité de la gestion est grande.

L'hypothèse de stratégies d'investissement statiques est vraisemblable pour la gestion traditionnelle. En effet, les investissements se font généralement de manière statique et directement sur les actifs sous-jacents. Les agrégations temporelles et spatiales nécessaires au calcul d'un rendement du portefeuille ne créent pas de non-linéarité. La volatilité est alors une mesure adaptée du risque d'un portefeuille. A l'inverse, les gérants alternatifs réallouent régulièrement leur portefeuille et utilisent des produits dérivés. Plusieurs types de stratégies hedge funds existent, et peuvent avoir un degré de dynamisme différent. Les hedge funds dits d'arbitrage visent à profiter d'inefficiences tout en restant neutres au marché. Les hedge funds directionnels ont un beta de marché périodiquement non nul mais proche de zéro sur un horizon de long terme. Les rendements résultants n'évoluent donc pas linéairement avec les rendements des actifs sous-jacents. Ainsi, une approche statique n'aidera pas à comprendre les risques de ces stratégies et il est logique qu'un actif standard n'explique pas les rendements des hedge funds.

Les hedge funds se distinguent également de la gestion traditionnelle par leur objectif d'investissement différent. Ils visent essentiellement à délivrer une performance absolue. Ils sont d'ailleurs qualifiés à ce titre de fonds "absolute return". Cette distinction donne lieu à des différences de profil de rendement-risque. Ackermann, McEnally et Ravenscraft (1999) [1] et Liang (1999) [71] ont montré que les hedge funds exhibaient des rendements ajustés du risque supérieurs, avec un niveau de risque idiosyncratique également supérieur. Ce résultat montre que la méthode classique d'évaluation de la performance fonctionne mal et n'arrive pas à expliquer la performance de ces fonds. Par construction, ces gérants visent à délivrer une performance absolue, c'est-à-dire décorrélée des facteurs de risque classique. La régression

statique proposée par Sharpe (1992) [93] n'est plus adaptée. De nombreux travaux de recherche proposent des évolutions spécifiques pour expliquer ces stratégies particulières. Lo (2001) [73] récapitule de façon exhaustive l'ensemble des raisons pour lesquelles il est difficile d'analyser ce type de fonds. Lo (2008) [76] propose une méthode de décomposition de la performance permettant d'identifier la vraie valeur du gérant de hedge funds, dans un contexte individuel c'est-à-dire sans comparaison à des facteurs de risque. Fung et Hsieh (1997) [48] confirment le comportement très différent des hedge funds et ajoutent au modèle classique des facteurs optionnels pour tenir compte de leur caractère dynamique. Fung et Hsieh (2001) [46], Agarwal et Naik (2001) [4] poursuivent ce travail d'explication des non-linéarités présentes dans les rendements des hedge funds. Agarwal et Naik (2004) [5] utilisent ce modèle afin d'expliquer plus particulièrement les risques de stratégies actions. Fung et Hsieh (2004) [47] formalisent ce modèle comme outil principal de benchmarking des hedge funds. Le modèle standard consiste à estimer de manière statique les expositions de la stratégie analysée à des facteurs eux-mêmes statiques ou dynamiques. Agarwal et Daniel (2009) [3], Agarwal, Arisoy et Naik (2015) [2], Agarwal, Ruenzi et Weigert (2016) [6] expliquent les performances des hedge funds par des expositions à un risque extrême, notamment présent sur les marchés actions. Bollen (2013) [24] confirme la difficulté d'explication des performances par un modèle factoriel, du fait des caractères à la fois dynamique et décorrélé de ces stratégies. Darolles et Mero (2011) [35] proposent une méthode de sélection dynamique de facteurs pour expliquer les rendements de ces stratégies en évitant la surspécification.

La complexité de certains actifs financiers les rend moins accessibles et donc moins échangés que certains actifs plus classiques tels que les actions. Ainsi, la liquidité des actifs détenus par les hedge funds est en général inférieure à celle des actifs possédés par des gérants d'actifs traditionnels. Les investisseurs dans ces stratégies subissent donc un risque supplémentaire.

Getmansky, Lo et Makarov (2004) [49] modélisent l'illiquidité des hedge funds par l'autocorrélation des rendements, résultat d'une valorisation *mark-to-model* et d'un comportement de lissage.

La gestion de l'asymétrie d'information dans la relation principal-agent a également un impact sur la tarification de la gestion, différente des standards observés pour la gestion classique. Des frais de performance s'ajoutent aux frais de gestion classiques. Payés lorsque les performances sont positives, ils permettent d'intéresser le gérant à la qualité de sa gestion, via ce revenu supplémentaire. Ainsi, principal et agent ont tous deux le même objectif. Une autre pratique commune dans l'industrie des hedge funds est la présence de capital propriétaire dans le fonds. Cela permet aux éventuels investisseurs de s'assurer que le gérant agit au mieux de leur intérêt, puisqu'il a un intérêt personnel à délivrer de la performance. Agarwal, Daniel et Naik (2009) [3] relient ces mécanismes visant à aligner les intérêts à une potentielle surperformance des hedge funds. Edwards et Caglayan (2001) [40] confirment leur résultat liant la surperformance à la présence de *skill*. Ozik et Sadka (2015) [84] étudient l'ensemble de ces conflits d'intérêt et confirment leur impact sur la performance. Hodder et Jackwerth (2007) [56] analysent le comportement stratégique de prise de risque des fonds qui visent à maximiser leur revenu, au détriment de la performance nette reçue par les investisseurs. Goetzmann, Ingersoll et Ross (2003) [50] identifient précisément l'impact de la clause *high watermark* sur le risque pris par le gérant et sur la valeur délivrée. Darolles et Gouriéroux (2015) [34] étudient l'impact de l'allocation entre comptes sur la performance affichée du hedge fund. Baker et Chkir (2017) [12] modélisent le caractère extrême des performances des hedge funds par des caractéristiques telles que le levier ou la liquidité.

Enfin, la littérature académique s'attache également à expliquer la per-

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formance des hedge funds via des caractéristiques statiques du fonds et non de l'investissement en lui-même. De nombreuses autres variables ont été considérées. Darolles (2014) [33] et Joenväärä et Kosowski (2015) [63] analysent l'impact de la structure juridique (UCITS ou non) sur la performance du fonds. Joenväärä, Karppinen, Teo et Tiu (2019) [62] analysent le contenu de la description textuelle des fonds et montrent que les hedge funds frauduleux ont des descriptions plus complexes. Cependant, Bollen, Joenväärä et Kauppila (2017) [25] montrent que toutes ces variables expliquant la performance des hedge funds ne permettent pas de prédire cette performance.

Une autre dimension d'analyse est la capacité des gérants à exécuter de manière optimale leurs transactions sur les marchés financiers. Frazzini, Israel et Moskowitz (2015, 2018) [44, 45], ainsi que Brière, Lehalle, Nefedova et Ramoun (2019) [26] mesurent le coût d'exécution des anomalies ou primes de risque des marchés actions. L'exécution de la stratégie de gestion est une problématique de liquidité de marché, mais les gérants doivent également tenir compte des mouvements de passif, relevant de la liquidité de financement. Teo (2011) [97] montre qu'il existe un risque d'inadéquation entre la liquidité à l'actif et celle au passif de certains fonds, et que ce risque engendre des performances moindres. Shleifer et Vishny (1997) [94] montrent de façon théorique que le risque de rédemption est la limite principale à la suppression complète des opportunités d'arbitrage. D'autres papiers s'intéressent à cette question de liquidité dans le cadre des fonds de fonds, comme Liu et Mello (2011) [72] et Agarwal, Aragon et Shi (2015) [2]. En plus de la question de liquidité, les fonds de fonds sont un cas intéressant car contiennent une deuxième couche de délégation, qui s'accompagne aussi de frais de surperformance. Darolles et Vaissié (2012) [36] analysent la valeur ajoutée pour les investisseurs.

## Les fonds de suivi de tendance

Les fonds de suivi de tendance, classés dans la catégorie des Commodity Trading Advisors (CTA), ou Managed Futures, sont des stratégies hedge funds particulières qui génèrent des questions spécifiques. La grande majorité des fonds CTA gèrent leurs portefeuilles au travers de produits futures. Les futures sont des produits à terme standardisés, impliquant pour l'acheteur une obligation d'acheter le sous-jacent à un prix donné à une date fixée. Certains d'entre eux sont adossés à un indice, comme ceux des marchés actions et obligations, ou à un taux de change. D'autres permettent d'accéder aux marchés de matières premières. Les suiveurs de tendance fondent essentiellement leur stratégie sur la présence de tendances sur les prix des actifs financiers. Or, cela va à l'encontre de l'hypothèse de marche aléatoire. Le modèle implicite des suiveurs de tendance implique que, sur une période de temps relativement longue, les rendements futurs soient de même signe que les rendements des tendances passées. Les modèles développés pour mesurer la performance des hedge funds au sens large se révèlent de moindre qualité lorsqu'on les applique aux fonds du style CTA.

Le rationnel économique justifiant la présence de tendances se trouve dans la théorie comportementale, proposée notamment par Kahneman et Tversky (1979) [64]. Le principe fondamental de cette théorie est de considérer que les participants de marché ne sont pas en tout temps rationnels, et prennent des décisions allant à l'encontre du principe de maximisation de l'utilité espérée. Grâce à une importante recherche en sociologie, on sait désormais que les investisseurs souffrent de biais comportementaux, par exemple l'ancre, le panurgisme ou la surréaction. Moskowitz, Ooi et Pedersen (2012) [82] récapitulent ces biais et associent à chacun un impact sur les prix. Ces biais ont pour conséquence d'éloigner le prix de sa valeur fondamentale : une



opposition a lieu entre limite d'arbitrage et forces comportementales. Barberis, Shleifer et Vishny (1998) [20] montrent que des écarts de valorisation perdurent du fait de ces limites. Lo (2004) [75] effectue un parallèle avec la biologie en comparant les différents acteurs économiques et financiers à des "espèces" qui ont pour objectif de survivre. La stratégie de suivi de tendance dispose donc d'un socle académique solide et qui prend de plus en plus d'ampleur.

Moskowitz, Ooi et Pedersen (2012) [82] et Hurst, Ooi et Pedersen (2013) [57] sont les premiers à étudier les caractéristiques empiriques des rendements issus des stratégies de suivi de tendance. Ils montrent la présence d'autocorrélation dans les rendements ajustés du risque de nombreux actifs financiers, répartis sur l'ensemble des classes d'actifs. De plus, ils observent la persistance de la performance de la stratégie de suivi de tendance. A la suite de ces travaux, une importante littérature issue du monde de la gestion d'actifs s'est développée. Elle vise à analyser la performance et établir les caractéristiques de cette stratégie. On peut citer par exemple Elaut et Erdos (2016) [41], Baltas et Kosowski (2012) [17], Hutchinson et O'Brien (2014) [60]. Côté académique, les modèles classiques de la littérature à savoir ceux de Fung et Hsieh (2001) [46] et Agarwal et Naik (2004) [5], intègrent des facteurs dynamiques visant à expliquer cette stratégie. Ils considèrent comme facteurs dynamiques des portefeuilles contenant des options exotiques (look-back straddles) visant à capter la variation maximale de prix subie par un actif sur une période pré-déterminée. La raison est qu'un suiveur de tendance qui se placerait de façon optimale (prédiction parfaite des changements de tendance) aurait donc ce profit. Cependant, ceci est remis en cause par deux éléments. Le premier est empirique. Le coût de l'option, appelée prime, réduit la performance globale. Le second est plus théorique. Les suiveurs de tendance ne cherchent pas à prédire le changement de tendance. De plus,

une réallocation mensuelle du portefeuille paraît peu fréquente au regard de la liberté et la facilité d'exécution de ces hedge funds, notamment ceux intervenant sur les marchés de futures. Il apparaît donc logique que leurs performances diffèrent de celles du portefeuille optionnel.

Au même titre, les modèles d'allocation classiques doivent être adaptés à ce nouveau cadre. La théorie moderne du portefeuille s'attache à définir un portefeuille optimal. Pour un niveau de risque donné, il est caractérisé par celui ayant le rendement espéré maximal. Cette théorie s'appuie sur la modélisation des comportements individuels et joints des actifs. L'hypothèse de normalité des rendements rend cette modélisation relativement simple, puisque seules moyennes et covariances sont à estimer. La remise en cause de cette hypothèse d'évolution des prix met en défaut les bases usuelles de construction de portefeuilles optimaux.

La dimension de coût d'exécution doit également être revue. Deux CTA employant la même stratégie sur le même univers d'investissement mais à un niveau de risque différent ont des positions égales, à un facteur multiplicatif près. Il existe également une relation de proportionnalité des positions avec la taille du fonds, mesuré par le montant d'actifs sous gestion. La mesure de turnover doit donc tenir compte de ces spécifications pour être un bon proxy de l'intensité à laquelle le gérant exécute des transactions. La question de la liquidité se pose différemment de celle dans un cadre actions, puisque les leviers individuel et global sont à discrétion du manager et doivent donc être pris en compte dans la mesure du coût d'exécution. La stratégie de momentum mise en oeuvre sur les actions génère un important turnover, bien supérieur aux autres facteurs tels que value ou size, comme le montrent Barroso et Santa-Clara (2015) [22]. Lesmond, Schill et Zhou (2004) [70] montrent que le turnover important génère des coûts de trading annulant les gains potentiels liés à l'anomalie. La construction de la stratégie de suivi de tendance

est certes différente car relève d'une approche directionnelle en *time-series* et non *cross-sectional* comme le facteur momentum classique, mais est fondé sur la même anomalie de momentum. Ainsi, le turnover attendu de cette stratégie est important. La question de l'implémentation est donc importante dans l'analyse de la performance de la stratégie. Les spécificités des fonds CTA, portant sur le modèle implicite des actifs financiers et sur les spécificités d'ordre opérationnel, sont autant d'arguments supplémentaires pour une analyse de performance spécifique de cette stratégie.

## Les travaux de la thèse

Cette thèse est la collection de trois travaux de recherche qui s'inscrivent tous dans le contexte des stratégies de suivi de tendance. Elle vise à mieux comprendre les risques et les performances de cette stratégie mais aussi à repenser sa construction. Deux phénomènes industriels récents ont en effet remis cette stratégie au centre des discussions. D'une part, les performances des quatre dernières années sont nettement inférieures à leur moyenne historique, ce qui soulève des questions sur la raison de l'anomalie, sur sa persistance dans le futur, et sa capacité à protéger contre les pertes des actifs traditionnels. D'autre part, l'avènement de la gestion systématique et des primes de risque alternatives a banalisé la stratégie. De nombreuses questions sont ainsi soulevées : est-ce que la stratégie offerte par l'industrie traditionnelle est une version simple, édulcorée, "beta", de la stratégie originale du trend following et est-ce la raison des moindres performances ? Est-ce que l'on peut vraiment parler d'une stratégie CTA ou alors est-ce que cet univers est hétérogène ? Du point de vue du signal, est-ce que les marchés financiers exhibent toujours des tendances ? Si oui, sous quelle forme ? Est-ce qu'un design optimisé, défini par une construction et une implémentation raffinées, redonne à la stratégie ses lettres de noblesse ?

Le premier chapitre s'attache à détecter la présence de tendances sur le marché, via l'exposition des fonds alternatifs à une version systématique, simple, répliquable de la stratégie de trend following. On confirme l'exposition aux tendances des deux stratégies directionnelles que sont le Global Macro et le CTA, et la quasi-absence sur les autres indices alternatifs, expliquant ainsi la différence de performance de ces deux types de stratégie lors de la crise. De plus, la construction hiérarchique de facteurs permet d'identifier plus précisément quelles sont les tendances jouées par ces stratégies. Cependant, l'utilisation d'un indice peut poser problème : des expositions potentielles des fonds le composant pourraient être diluées et disparaître lors de l'aggrégation. Certains fonds individuels, dont la description indique une catégorie différente de CTA, sont partiellement exposés aux tendances. Ils paient une prime pour s'assurer contre un risque extrême, rapprochant le suivi de tendance à un produit d'assurance. Cependant, la performance moyenne des fonds labellisés CTA apparaît supérieur à cette prime. Ainsi, externaliser ce type de couverture auprès de fonds spécialisés semble optimal en termes de valeur économique.

Le second chapitre vise à comprendre la forme des tendances sur les marchés financiers, et la commonalité entre tendances observées simultanément sur plusieurs marchés. Nous montrons qu'il existe des liens entre des actifs financiers issus de classes d'actifs différentes plus forts que certains liens entre des actifs de même classe. La perception du risque pour une stratégie de trend following doit être différente de celle d'une approche plus statique, étant naturellement exposée aux tendances communes. Une analyse factorielle classique permet d'extraire un facteur de risque systématique de rupture de tendance. Des styles alternatifs, différents de ceux exposés au facteur de suivi de tendance du premier chapitre, sont expliqués par une exposition à ce nouveau facteur.

Le troisième chapitre approche l'analyse des performances récentes de la stratégie par l'angle de son coût d'exécution, mis de côté dans les modélisations des chapitres 1 et 2. L'exécution de transactions est nécessaire afin de posséder le portefeuille théorique, mais implique des coûts, explicites et implicites. Les premiers sont ceux prélevés de manière fixe par les contreparties nécessaires à l'exécution et au suivi de la transaction. Les seconds sont liés à l'impact de l'activité même de trading sur les prix, et relèvent donc de la notion de liquidité. La liquidité réelle perçue par un investisseur se mesure par le coût d'exécution du portefeuille, et dépend finalement peu du coût effectif d'une transaction. En effet, les décisions prises par le gérant pour veiller aux contraintes de risque du fonds sont prépondérantes dans le coût d'exécution. Les conditions de marché récentes, symbolisées par une qualité de tendance moindre et une baisse de la volatilité générale des marchés, impliquent un turnover plus important. C'est ce qui explique principalement la hausse des coûts de transaction. L'exécution individuelle reste de qualité, confirmant la liquidité des marchés de futures utilisés.

# Chapter 1

## Trends Everywhere? The case of hedge fund styles

This chapter investigates empirically whether time-series momentum returns can explain the performance of hedge funds in the cross-section. Relying on the trend following literature, a volatility-adjusted time-series momentum signal is applied on a daily basis across a large set of futures, covering the major asset classes. We build a hierarchical set of trend factors: the full version TREND can be split in summable factors across two dimensions, the horizon of the signals and the traded asset class. We show that Managed Futures, Global Macro and Fund of Hedge Funds strategies can be partly explained by a TREND exposure. Moreover, a TREND exposure is a significant determinant of hedge funds returns at the fund level, for Managed Futures and Global Macro but also, and more surprisingly, for other styles.

*Keywords:* Managed Futures; Time series momentum; Trend-following; Commodity Trading Advisor (CTA); Hedge funds; Trading strategies.

## 1.1 Introduction

During the 2008-2009 Global Financial Crisis (GFC), hedge funds suffered heavy losses, raising doubt about their ability to deliver absolute and uncorrelated returns. However, some strategies such as trend following performed particularly well. The questions are: what differentiates these funds from the ones that went down? Are these funds exposed to specific trend risk premia? Can this strategy be used to build diversified portfolios?

Following the crisis, there was a strong desire for all parties involved to better understand hedge funds, in terms of transparency and in terms of sources of returns. Up to now, there has been attempts to explain the hedge funds performances but results were not convincing for Managed Futures. This is all the more surprising since the first dynamic factors included in a factor model were specifically designed to understand trend following funds. Indeed, their systematic feature should make the strategy easily replicable but empirical tests do not confirm it.

In this paper, we build a new hierarchical set of factors, harvesting the trends in the financial markets, and look at their presence in the cross-section of alternative strategies. We define a framework in which the global factor TREND can be transparently derived into an allocation of sub-versions of the factor. The standard way to decipher hedge fund strategies is through a linear factor model, where past returns of a strategy are projected on a series of known factors. First, we check whether our TREND factor is strongly priced among Managed Futures funds, also called Commodity Trading Advisors (CTAs). Indeed, most of them are systematic and apply a trend-following strategy. Secondly, we test if other hedge fund strategies have a trend exposure, to confirm what we observe during the GFC. The standard factor model in the literature comes from Fung and Hsieh (2001) [46] who create options factors, monthly-reshuffled lookback straddles written on the follow-

ing five common asset classes: Bonds, Currencies, Commodities, Equities and Interest Rates. What sets us apart lies in the construction of dynamic, diversified factors, that can go long and short, and harvest all types of trends: from short term to long term ones. We test several specifications to check if some hedge funds are more exposed to a specific type of trends. We confirm that CTAs have a statistically and economically significant exposure to our TREND factor, both at the index and fund levels. This result holds when adjusting for the standard risk factors, and for different index providers. The second result at the index level is that Global Macro funds have a strong exposure to our TREND factor, perhaps due to their cross-asset feature and to their objective to time markets or trends. Apart from fund of funds, betas are not significant in the rest of the alternative space, confirming this could be the reason for their low performance during the GFC.

The second result is that our TREND factor is priced in the cross-section of individual hedge funds. The interpretation of the quantile portfolios returns is twofold: the "premium" is negative when the analysis is performed on raw returns and turns positive when controlling for other known risk factors. We analyze whether it is possible to classify individual hedge funds outside the Managed Futures space based on their TREND beta. An increase in the loading is associated to a lower overall annual return but a lower maximum drawdown, relating the CTA investment to an insurance profile. Firstly, our paper helps understanding the difference in performance during the 2008 crisis by showing a TREND factor is strongly priced in some but not all hedge funds styles. Our hierarchical approach enables to dig deeper in the strategies and see what are the hidden trend exposures across styles. Finally, funds are rewarded on risk-adjusted terms by exposing to trends.

This chapter helps demystifying the CTA space, but not only. By differentiating funds according to their Trend(s) exposure, one can better understand the contribution of each constituent of a Managed Futures funds' portfolio.



Indeed, thanks to this model, a trend exposure can be computed for each constituent and then linearly aggregated to get the result at the portfolio level. This risk management benefit holds when going one step higher in terms of allocation of capital. Indeed, the trend exposure of a portfolio of hedge funds can be better monitored: hidden trend exposures outside the Managed Futures space can be extracted and can now be taken into account when allocating between hedge fund styles.

The remainder of the chapter is organized as follows. Section 1.2 describes the relevant literature. Data and factor construction are presented in Section 1.3. Our empirical methodology and the results are provided in Sections 1.4 and 1.5. In Section 1.6 we examine the robustness of our results. Section 1.7 reviews our arguments and concludes the paper.

## 1.2 Literature review

Our research is firstly related to the literature on hedge fund performances. We focus on the alternative space and more specifically the relevant factor models developed to understand these returns. Thanks to the Capital Asset Pricing Model (CAPM), Sharpe (1964) [91] performs the first style analysis of mutual funds. Mutual funds returns are divided into systematic returns coming from the market exposure and idiosyncratic returns, related to the ability to select stocks. Indeed, many researchers were able to prove the existence of a significant alpha, thus contradicting the CAPM, but all attempts were nipped in the bud with the apparition of risk factors. Fama and French (1996) [42] extend the CAPM with two new factors: size and value. CAPM and Fama-French models can be used to assess the risk exposures of a portfolio. The beta is the exposure of the portfolio to this risk factor. In the equity market, the risk factors are generally designed as portfolios replicating a philosophy of investing, a style: for example growth, value, small cap

and momentum. Contrary to the former, the latter takes advantage of an anomaly in the equity market discovered by Jegadeesh and Titman (1993) [61]: going long the winners and short the losers delivers alpha. Carhart (1997) [28] adds this cross-sectional momentum factor into the standard risk model.

Hedge funds are different from mutual funds: they can short sell, use leverage, trade options and have access to alternative asset classes. Thus, the equivalent of the CAPM for alternative investments would be a model where all asset classes are put as covariates. Still, such a static model won't capture neither the ability to leverage nor the volatility exposure. Moreover, hedge fund managers trade more frequently than traditional managers. The investment process is no longer a buy-and-hold one.

Return-based style analysis in this space refers to the technique of linear factor models. First, seminal contributions on this matter come from Fung and Hsieh (2001, 2004) [46, 47], Agarwal and Naik (2001,2004) [4, 5] and Ben Dor and Jagannathan (2003) [38], all trying to understand hedge fund performances by analysing the cross-variation between their returns and other strategies' returns. Fung and Hsieh (2001, 2004) [46, 47] propose seven (even nine in further work) risk factors to explain the hedge fund performances. They include the main asset classes: equity (equity market, size), fixed income (bond, credit) and emerging markets to account for the cross-asset dimension of hedge funds and three proxies of trend-following strategies on bonds, currencies and commodities (lookback options) to account for their dynamic exposures. They first focus on trend-following funds and then extend their scope to all alternative strategies. Focusing on volatility, Agarwal and Naik (2004) [5] include volatility exposure through put options, written on the S&P500 index to explain the differences in returns across the alternative styles. Hasanhodzic and Lo (2007) [55] use observed factors, such as the S&P 500 index, the USD return index, the Bond Index, to model the returns

of individual hedge funds for cloning purposes.

Despite their strong economic support, these models do not perform particularly well in explaining some hedge fund styles, and in particular trend-following strategies. Firstly, these hedge fund factor models can be doubted on their assumptions. Indeed, these models have one main drawback: the estimation of the betas can lead to wrong interpretations. Despite their convexity, the option-based factors of Fung and Hsieh cannot capture all the non-linearities in hedge fund payoffs, resulting in wrong estimations of betas. De Roon and Karehnke (2017) [37] confirm that "this approach in general does not suffice because option-like payoffs can still generate a positive alpha at the expense of negative skewness". They focus on a solution considering skewness to alleviate it. Another bias is the time-varying dimension of the loadings. Indeed, as stated before, hedge funds can dynamically allocate to different risk factors and fixing ex ante a specification does not permit to capture this. A more dynamic model, which would allow betas to vary, might be needed. Indeed, Patton and Ramadorai (2013) [86] show that hedge funds exposures vary across and within months, confirming the relative high frequency behaviour. They have access to daily returns of a set of HFR indexes. However, hedge funds report only monthly net asset values (NAVs), making the model not applicable in practice. Also, time-varying beta estimation would require very long samples, which is usually not the case for monthly returns. Betas could vary but more generally, the set of risk factors that an hedge fund decides to expose to might change. Darolles and Mero (2011) [35] propose a selection algorithm to keep only the most relevant risk factors in a time-varying setup.

Secondly, the Fung-Hsieh factor model does very well at explaining the equity-related alternative strategies, such as Long/Short Equity and Market Neutral but results are somewhat less robust on fixed income-related ones and to a larger extent, cross-asset strategies such as macro ones. Focusing on

CTA strategy, Elaut and Erdos (2016) [41] confirm that "the performance of these models in explaining Managed Futures funds' return is, however, lackluster".

In addition, there are some interesting papers proposing additional factors, with a strong economic rationale, aiming at demystifying hedge fund performances. Mitchell and Pulvino (2001) [80] focus on risk arbitrage, Sadka (2009, 2011) [89, 90] on a liquidity factor, Bali (2014) [13] on an uncertainty indicator while Buraschi (2013) [27], Arisoy, Agarwal and Naik (2015) [2] work on volatility and correlation risks. Agarwal et al. (2009) [3] and Agarwal et al. (2016) [6] form factors based on higher moments of the distributions, with a focus respectively on stocks and holdings, and show it is priced in the cross-section of hedge funds. Hedge funds are not only exposed to these risk factors but also to the standard market, as shown by Patton et al. (2009) [85]. Thus, the asset class factors of Fung and Hsieh are necessary in the factor model. Recently, a strong interest rose about a cross-asset carry factor, with works from Kojien et al. (2016) [67] and Baltas (2017) [16]. Most of these factors are the result of an economic rationale, either by a pure risk argument, or by means of institutional constraints. They rely on being long some assets and short others, hoping for a reduction in the spread, which is the essence of arbitrage. The famous adage, from the book "When Genius failed" by Roger Lowenstein qualifies them perfectly: it's like "picking up pennies in front of a steamroller". On the contrary, the trend following strategy has a rather different profile, with a right skewness (many small losses and few large gains), taking advantage of the trends in the markets caused by the behavioural biases of investors. Thus, all these factors are very helpful to understand the cross-section of hedge funds but not specifically on directional strategies.

Finally, we turn to papers from academic researchers with an industry partnership. There are some attempts at building trend following benchmarks in

the industrial side of the academic literature. Indeed, Moskowitz, Ooi and Pedersen (2012), with AQR, develop the concept of “time-series momentum”; UBS, RPM and Aspect Capital are also connected to academic researchers’ work on this matter. Moskowitz, Ooi and Pedersen (2012) [82] document serial correlation in the risk-adjusted returns across the major asset classes, and show that a simple “time-series momentum” (hereafter named TSMOM) can harvest this alpha. Their construction is similar to ours, except that they focus on the 1-year lookback with a monthly rebalancing. The cross-sectional version is applied within the equity asset class and is market neutral, the portfolio being long the winners and short the losers. Conversely, the time-series momentum is applied on futures of different asset classes, and is long or short each of them regardless of the asset class. No cross-sectional comparison is done to determine the position.

Hurst, Ooi and Pedersen (2013) [57] work on the economic intuition behind the presence of such trends in the financial markets. It is a major breakthrough: the random walk hypothesis and the related Efficient Market Hypothesis are strongly challenged. Based on the recent field of behavioural finance, Barberis, Shleifer and Vishny (1998) [20] show investors are not perfectly rational, suffer from multiple behavioural biases which create market inefficiencies. The most famous are herding, anchoring and confirmation biases. For further information, refer to Hurst, Ooi and Pedersen (2013) [57] who propose a very thorough review of such biases and the associated mechanisms that create trends. In addition, they show TSMOM helps to understand Managed Futures indexes and individual funds. Simultaneously, Baltas and Kosowski (2012) [17] also document a time-series momentum as a benchmark for trend-following funds. The construction methodology is similar to the one used by Moskowitz and his co-authors, as well as the proof of autocorrelation in the risk-adjusted returns. In addition, they study fund flows in the CTA industry and assess whether they suffer from capacity con-

straints or not, despite only trading futures contracts. Baltas and Kosowski (2015) [19] focus on the impact of the volatility and correlations on the performances of the time-series momentum factor. Hutchinson and O'Brien (2015) [59] relate trend-following returns to the periods of crisis and show that post-crisis returns are usually weak/below average. Elaut and Erdos (2016) [41] build a trend-following benchmark mixing the diversified TSMOM across a large set of lookback horizons and show it improves the understanding of individual CTAs in comparison to the standard trend-following benchmarks [17, 82]. Industry also did its part in this benchmarking mission when Société Générale (formerly NewEdge) published CTA and Trend indexes, which are baskets of actual funds, as well as a factor, the Trend Indicator. This chapter aims at filling this gap: use industrial and academic ideas to build a new risk factor synonym of trend and to better understand the cross-section of hedge funds strategies. Do we detect trend everywhere in the hedge fund space?

## 1.3 Data and methodology

In this section, we first describe the various datasets involved in the empirical illustration, namely, futures' prices, standard hedge fund factors from the literature, as well as hedge funds indices and individual funds' returns. Secondly, we document the construction methodology of our hierarchical set of factors.

### 1.3.1 Data

#### Futures

Our sample consists of 50 futures, across five asset classes: 19 commodities, 12 equity indices, 9 bonds, 7 currencies and 3 short-term interest rates. These instruments are among the most traded and liquid contracts. Since

our benchmark construction will be on a daily frequency, we want to remove any illiquidity issue (price impact and price significance) as much as possible by applying the following procedure. For each of them, we record 4pm UTC and closing prices across all the front-month contracts that are rolled over to build the continuous time series. Indeed, futures have an expiry date so need to be put together to form a continuous time series that represents the returns of a static exposure. The roll calendar is based on liquidity, and a forward ratio price adjustment is performed to avoid any gap in the series due to backwardation or contango structure.<sup>1</sup> In accordance with Moskowitz et al. (2012) [82] who look at the observed daily volume, the front-month contract is always the most liquid. All contracts were not traded during the full sample, making the universe of tradable contracts for our strategies start from 38 contracts in 1990 to reach 50 contracts in 2007. All futures' starting date are shown in Table 1.1. The list of contracts we use is similar to what can be found in the trend following literature [17, 82].

Table 1.1 also presents univariate statistics for futures contracts returns. The results are highly heterogeneous in many aspects: annualized return spans from -22% for the natural gas to almost 8% for the soybean meal, whereas annualized volatility reaches 46% for the natural gas and is as low as 0.37% for Euribor. Thus, 1\$ invested in an interest rate market is not as risky as 1\$ invested in a commodity market. We need to correct by the differences in volatility to have a similar risk contribution by market. According to Getmansky, Lo and Makarov [49], the presence of auto-correlation in hedge funds monthly returns indicates illiquidity, or even a smoothing behavior. Indeed, funds that invest in illiquid assets such as Private Equity can be forced to use mark-to-model valuations instead of mark to market, resulting in smoothed net asset values. Here, the first-order autocorrelation is low and

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1. Backwardation and contango refer to the two possible shapes of a futures curve, the first relates to when the futures price is below the expected spot price and the opposite for the latter.

not significant across all futures, which confirms the liquidity of this type of contract. Futures markets have a fundamental role in the price discovery process. Thus, it is possible to implement a dynamic strategy, which can switch position on a day-to-day basis. Also, the return distributions of some futures are highly asymmetric with fat tails when others have a distribution similar to a bell curve.

### **Asset pricing benchmark**

We use in our analysis the nine-factor model from Fung and Hsieh (2001) [46]. In their seminal paper, they show these factors have strong explanatory power for most hedge fund indexes. Specifically, they contain four asset class factors, being Buy-and-Hold (B&H) portfolios of major indexes, two equity-oriented and two qualified as fixed-income. The first factor is the S&P500 index returns (now referred as Equity), a second is its spread with the Russell 2000 index (now referred as the Size risk factor). Another is constructed using the 10-year T-Bond yield, standing for the Bond exposure, and the last one is the Credit exposure, based on the spread with Moody's BAA bonds and the previously cited Treasury index. To account for the optionality and the dynamics of hedge funds' exposures, they added trend following risk factors, built as portfolios of lookback straddle options. Initially, there were only three of them, for these three underlyings: currencies (PTFSFX), commodities (PTFSCOM) and bonds (PTFSBD). They further added similar versions on interest rates (PTFSIR) and equity market (PTFSSTK). All these data were taken from Fung and Hsieh website.<sup>2</sup>

### **Hedge fund data**

Our dataset comprises eleven HFR indexes, spanning from Equity Market Neutral to Global Macro. The full list, along some description of the

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2. <http://faculty.fuqua.duke.edu/dah7/DataLibrary/TF-FAC.xls>



indexes, is available in Table A7 in Appendix. Monthly returns are available from January 1990 until December 2016. As a robustness check, we also have a selection of Credit Suisse First Boston (CSFB) indices, available from January 1994 to October 2016. The selection was done to have a similar set of strategies as in our HFR database. In both cases, returns in excess of the risk-free rate, set as the Euribor 3M, were calculated.

To analyse the commonality of returns between our Trend factor and hedge fund performances, we collected individual funds' returns from the Euro-Hedge Database. Our original dataset contains 3,696 funds across various alternative strategies. Some fund characteristics are available such as the fee structure, assets under management, inception date and some information related to the management firm. As standard for all hedge fund databases, reported returns are net-of-fees and monthly. The Managed Futures category contains 521 funds, and 425 of them are in USD currency. Cleaning was performed and additional data (fees information) from Bloomberg was retrieved. Monthly gross-of-fees returns were calculated based on the fee schedule and a quarterly crystallization, unless otherwise stated. Management fee was increased by 0.25% annually to account for expense fees. Our dataset starts in December 1993 and ends in June 2017. At least 50% of the funds actively traded past January 2011, which will stand for the start of the sample used in the analysis.

Table 1.2 presents the average monthly return of the HFR indexes. We split the complete period into two periods, pre- and post-GFC crisis: from December 1993 to March 2009 for the pre-crisis subperiod and April 2009 to July 2017 for the post-crisis subperiod.<sup>3</sup> Systematic Diversified and Macro indexes were among the most performing ones before March 2009, but also the ones that suffered the most after the GFC. Conversely, non-directional

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3. Our definition of sub-periods is based on Edelman et al. (2012) [39], who identify March 2009 as a structural break point associated with the end of credit crisis.

strategies such as Convertible Arbitrage, Relative Value, Equity Market Neutral experienced a lower performance variation, which was even positive for the first mentioned.

Table 1.3 contains the main statistics of the HFR indexes computed over the period when Fung and Hsieh factors are available (hereafter called "FH period"), that is from January 2010 to March 2016. There is strong cross-section variation in the returns and sharpe ratios in the hedge fund space, highlighting the different risk profiles of these strategies. Assuming Systematic Diversified and Global Macro strategies can be leveraged, they would exhibit a lower maximum drawdown compared to the rest of the hedge fund space, which in particular results from their GFC behavior.

### 1.3.2 Factor construction

Two main principles drive the construction of our factors, concerning two different types of trends. First, the major trends across asset classes need to be captured, thus we build a TREND factor (similar to a top-down approach) that harvests them. Secondly, the trends within a given asset class (similar to a bottom-up approach) are harvested through the *sector*-TREND factors. Another aspect is related to the timeframe of the trends: short-term (ST) as well as long-term (LT) trends need to be taken into account. The global TREND portfolio is positioned according to the mean of individual signals, and the *horizon*-TREND portfolios focus on one timeframe each. To reach these objectives, we construct our trend risk factor based on the practice of hedge funds and especially systematic CTAs. The construction is cross-section-diversified since invested across asset classes, and time-diversified due to its dynamic trend timing nature. We expect its returns to be correlated with hedge funds indices as well as individual CTAs performances. Indeed, many CTAs employ trend following strategies over different horizons: some are short-term (around 1 month holding period), some medium-term (from

6 months to 1 year) and some long-term (more than one year). Specialized CTAs trade only commodity markets, or focus on one horizon, but we hope to understand returns of all kinds of CTAs thanks to our sub-Trend factors. The risk factor is in fact an equal-weight basket of five time-series momentums, each diversified across futures, with daily rebalancing, with a lookback horizon: 20, 65, 130, 260 and 520 trading days respectively. These windows were chosen to fit standard calendar splits (one month, three months, six months, one year and two years) to keep it simple and assuming trend signals used by actual CTAs might be set up that way. Despite showing serial correlation over different lookbacks, Moskowitz, Ooi and Pedersen (MOP, 2012) [82] focus on the 1-year lookback to build their time-series momentum (TSMOM). Baltas and Kosowski (BK, 2012) [17], as well as Elaut and Erdos (EE, 2016) [41], mix different time horizons when constructing their trend following benchmark. The first mix monthly, weekly and daily rebalanced portfolios, each with a different lookback, to construct their Futures-based Trend Following benchmark (FTB). Like us, the latter proposes a more “dynamic” one, due to a daily rebalancing, but with as much as 251 different lookbacks (ranging from 10 to 260 days). In an ad hoc analysis, we study the relationships between time-series momentum strategies which differ by the lookback they use and we find the “loss of information”, as measured by the correlation, is proportional with the log-difference in lookback. Thus, to avoid over-fitting, we selected the five most informative lookbacks, being the ones mentioned above.

We assume daily rebalancing as the futures in our dataset are ones of the most liquid contracts, thus reducing any potential friction costs. For the same reason, CTAs are known to be agile and can switch their position from one day to the other, and monthly rebalanced portfolios would not have been able to capture their returns. Let us introduce two signal notations. The first one is  $s_{i,t,h_j}$ , and refers to a momentum signal at date  $t$  for a

market  $i$  over a period  $h_j$ .  $s_{i,t,h_j}$  is equal to 1 if the price on date  $t$  is higher than the price  $h_j$  days before, and -1 otherwise. In the global TREND construction, we take the average of five signals with the respective lookbacks  $h_j \in \{20, 65, 130, 260, 520\}$  to build the global signal  $S_{i,t}$ . The mathematics are the following:

$$S_{i,t} = \overline{\text{sign}(p_{i,t} - p_{i,t-h})} = \frac{1}{n_s} \sum_{j=1}^{n_s} \text{sign}(p_{i,t} - p_{i,t-h_j}) = \frac{1}{n_s} \sum_{j=1}^{n_s} s_{i,t,h_j} \quad (1.1)$$

The construction of our factors is standard in the trend following literature, represented by MOP (2012), BK (2012) and EE (2016):

$$r_t^P = \frac{\kappa}{N_t} \sum_{i=1}^{N_t} S_{i,t-1} \frac{r_{i,t}}{\sigma_{i,t-1}} \quad (1.2)$$

where  $S_{i,t-1}$  is the average  $\overline{\text{sign}(p_{t-1} - p_{t-1-h})}$ , where each component is the momentum signal on the past  $h$  trading days, for  $h$  in  $\{20, 65, 130, 260, 520\}$ ,  $\sigma_{i,t-1}$  is the realized volatility<sup>4</sup> of future  $i$ ,  $N_t$  is the number of actively traded contracts at date  $t$ ,  $r_{i,t}$  is the return of future  $i$  at date  $t$ ,  $\kappa$  is the individual target volatility. As explained in the data section, not all futures trade for the whole period, making the number of contracts available for trading time-varying. Signal and volatility, constituting the position, are just lagged one day since we use 4 pm UTC prices, making instantaneous execution possible. Indeed, with closing prices data, one would wait for the settlement to calculate signals, pushing the trading on the next day. We assume signals are calculated at 4 pm and execution is done simultaneously. The individual target volatility  $\kappa$  is set to target a 10% annual volatility per future, but the

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4. Instead of using the volatility, we can also build the factor by considering the risk contribution of each market to the final portfolio. In that case, some information on the correlations between assets would be included in the factor construction. It could be a way to get at the end of the process a more balanced factor, when the number of markets across asset classes is heterogeneous.

diversification between futures reduces the portfolio volatility.<sup>5</sup>

To develop the intuition on this factor, let us assume that we consider 5 futures: three on the equity markets and two on the bond markets. We first have to compute on each of the five markets the elementary time series momentum signal  $s_{i,t,h_j}$  for different horizons  $h$ , and then average them to get a unique signal per futures market. In a second step, we build a portfolio of the five markets, the weight of each market being inversely proportional to its volatility  $\sigma_{i,t-1}$ . We observe with this example that the initial choice of the investment universe is crucial in the definition of our TREND factor. Here we overweigh in a way the equity asset class in choosing a higher number of equity markets.

This strategy can be applied to a different set of futures, for example, if we were to select only the  $N_{t,Equity}$  equity futures, we would get a version of Trend on the Equity asset class. Finally, TREND is only an allocation of the "sub"-TREND factors built on the different asset classes. This property also applies when decomposing across lookbacks. Let's look at the mathematics of such decompositions.

First, we note  $\Omega_t$  the universe of tradable futures at date  $t$ , and  $N_t$  its corresponding cardinality. We can partition it into  $n_\Psi$  sectors, which are essentially asset classes:

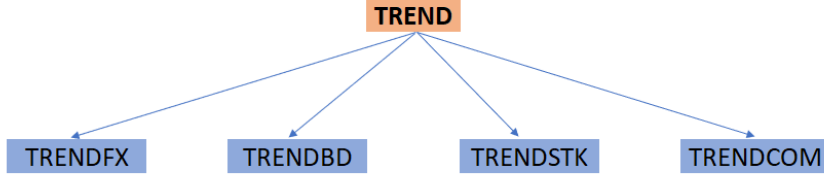
$$\Omega_t = \{\Psi_{j,t}, j = 1..n_\Psi\} \tag{1.3}$$

Each sector  $j$  has its own time-varying cardinality:  $N_{\Psi_{j,t}}$ . At any date  $t$ , we have the following relation between cardinalities, due to the property of

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5. In addition, the numerator (the signal) is equivalent to the average of log returns over the window, and the denominator (the volatility) is the standard deviation around this mean. So, both components are orthogonal by construction.

Figure 1.1 – Diagram of the asset class decomposition of the TREND factor.



partition of the universe:

$$N_t = \sum_{j=1}^{n_\Psi} N_{\Psi_{j,t}} \quad (1.4)$$

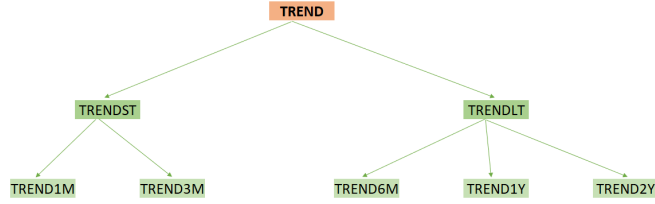
Let's start from the market level formulation:

$$\begin{aligned} r_t^{\Omega_t} &= \frac{1}{N_t} \sum_{i=1}^{N_t} S_{i,t-1} \frac{\kappa}{\sigma_{i,t-1}} r_{i,t} = \frac{1}{N_t} \sum_{j=1}^{n_\Psi} \sum_{i \in \Psi_{j,t}} S_{i,t-1} \frac{\kappa}{\sigma_{i,t-1}} r_{i,t} \\ &= \sum_{j=1}^{n_\Psi} \frac{N_{\Psi_{j,t}}}{N_t} \frac{1}{N_{\Psi_{j,t}}} \sum_{i \in \Psi_{j,t}} S_{i,t-1} \frac{\kappa}{\sigma_{i,t-1}} r_{t,i} = \sum_{j=1}^{n_\Psi} \frac{N_{\Psi_{j,t}}}{N_t} r_t^{\Psi_{j,t}} \end{aligned} \quad (1.5)$$

The TREND portfolio is an allocation of the sector-TREND portfolios, with the weights being the fraction of the number of futures per sector divided by the total number of futures available at date  $t$ . Figure 1.1 presents the decomposition.

In our case, sectors are asset classes, resulting in the five following factors: TRENDFX on Currencies, TRENDDBD on Bonds and Interest Rates, TRENDSTK on Equity indices, TRENDCOM on Commodities. The importance of a given asset class is proportional to the number of available liquid futures. The underlying assumption is that, once risk-adjusted, all the markets are viewed as equal, their asset class is foregone. A consequence is that more money is allocated to sectors with a large number of futures, assuming more capacity. This assumption is not problematic for two reasons: all selected futures are among the most liquid and our factor is gross of transaction

Figure 1.2 – Diagram of the signal decomposition of the TREND factor.



costs, so there is no impact of the hypothetical AUM on the factor returns.

After explaining the market decomposition, let's focus on the signal decomposition.

$$\begin{aligned}
 r_t^{\Omega_t} &= \frac{1}{N_t} \sum_{i=1}^{N_t} S_{i,t-1} \frac{\kappa}{\sigma_{i,t-1}} r_{i,t} = \frac{1}{N_t} \sum_{i=1}^{N_t} \left( \frac{1}{n_s} \sum_{j=1}^{n_s} s_{i,t-1,h_j} \right) \frac{\kappa}{\sigma_{i,t-1}} r_{i,t} \\
 &= \frac{1}{n_s} \sum_{j=1}^{n_s} \frac{1}{N_t} \sum_{i=1}^{N_t} s_{i,t-1,h_j} \frac{\kappa}{\sigma_{i,t-1}} r_{i,t} = \frac{1}{n_s} \sum_{j=1}^{n_s} r_{t,h_j}^{\Omega_t}
 \end{aligned} \tag{1.6}$$

The TREND portfolio is in fact an equal-weight allocation of the horizon-Trend portfolios, portfolios whose signal is based on only one lookback each. The five factors will be noted: TREND1M, TREND3M, TREND6M, TREND1Y and TREND2Y. Figure 1.2 shows the structure of the signal decomposition, with an additional layer corresponding to the following partition:

$$\{20, 65, 130, 260, 520\} = \{20, 65\} \cup \{130, 260, 520\} = ST \cup LT \tag{1.7}$$

This property of decomposition, across sectors and lookback windows, allows to satisfy both the macro and the market dimensions objective and to better understand the types of trends present in the hedge fund space.

Table 1.1 – Summary statistics of some of our continuous futures. *Note: Ann. return refers to the annualized return in %, annualized volatility, value-at-risk (VaR) and maximum drawdown (MDD) are also expressed in %, S and K stand for skewness and kurtosis, whereas  $\rho$  is the first-order autocorrelation. Statistics were calculated on the period starting on the first trading date (FTD) until 2017-12-31 for each market.*

	Ann. Ret.	Vol.	VaR (95%)	MDD	S	K	$\rho$	FTD
Emini_DJIndex	6.13	16.35	1.49	-53.65	-0.06	15.06	-0.02	2002-04-05
Emini_SP500	4.22	18.26	1.71	-63.47	-0.24	11.59	-0.02	1997-09-10
Eurostoxx50	1.40	22.79	2.27	-68.16	-0.15	7.19	0.02	1998-06-23
DAX	4.79	21.80	2.13	-75.30	-0.30	8.71	0.03	1990-11-26
SMI	3.28	17.82	1.69	-57.06	-0.34	10.57	0.06	1998-10-14
Footsie	2.50	17.05	1.68	-57.17	-0.17	7.37	0.02	1990-01-03
CAC40	3.08	21.20	2.09	-67.20	-0.09	7.15	0.02	1990-01-03
US10YTnote	3.46	5.84	0.59	-14.06	-0.14	6.01	0.02	1990-01-03
US2YTnote	1.35	1.58	0.16	-4.46	0.06	7.76	0.02	1990-06-26
US5YTnote	2.57	17.80	0.40	-46.07	0.01	23.40	-0.48	1990-01-03
Bobl	2.69	3.06	0.31	-8.29	-0.24	5.22	0.01	1991-10-07
BundDTB	3.97	5.12	0.52	-11.58	-0.21	4.92	0.02	1990-11-26
Schatz	0.82	1.16	0.12	-4.63	-0.31	7.49	0.05	1997-03-10
EuroDollar	0.52	0.64	0.06	-2.47	0.49	21.58	0.08	1990-01-03
Euribor	0.23	0.37	0.03	-2.28	0.88	20.33	0.16	1999-01-11
CHF_USD	0.67	11.36	1.12	-51.01	0.94	27.62	0.01	1990-01-03
EUR_USD	-0.06	9.69	0.99	-35.54	0.17	5.39	0.02	1998-11-16
GBP_USD	0.84	9.51	0.92	-40.61	-0.30	9.84	0.04	1990-01-03
JPY_USD	-0.97	10.71	1.05	-62.81	0.57	9.63	0.00	1990-01-03
Corn	-6.92	24.84	2.48	-90.09	0.05	7.85	-0.02	1990-01-03
Soybeans	2.56	22.17	2.18	-51.62	-0.20	6.65	-0.02	1990-01-03
Wheat	-10.54	27.42	2.73	-97.47	0.16	6.13	-0.04	1990-01-03
Cocoa	-3.84	28.34	2.88	-91.04	0.13	6.09	0.01	1990-01-03
Sugar11	-1.22	30.38	3.09	-73.76	-0.19	5.56	-0.01	1990-01-03
Copper	4.65	24.56	2.44	-67.60	-0.19	6.97	-0.01	1990-01-03
Gold	1.37	15.64	1.50	-62.76	-0.28	10.48	0.01	1990-01-03
Silver	0.63	27.43	2.68	-73.66	-0.34	9.71	0.01	1990-01-03
Platinum	2.35	20.33	1.99	-67.23	-0.47	7.93	0.05	1990-01-03
CrudeOil	-0.08	34.25	3.34	-93.34	-0.86	19.56	0.01	1990-01-03
NaturalGas	-22.48	46.45	4.68	-99.86	0.07	6.02	-0.01	1990-04-04



Table 1.2 – Average monthly return (expressed in %) of the HFR indexes on the periods running from December 1993 to March 2009 (Before GFC) and from April 2009 to July 2017 (After GFC).

	Before GFC	After GFC
Equity Market Neutral	0.54	0.24
Equity Quant. Directional	0.92	0.51
Equity Short Selling	0.38	-0.99
Fund of funds	0.46	0.30
Systematic Diversified	0.98	0.18
Convertible Arbitrage	0.52	0.77
Fixed Income Multistrat.	0.50	0.57
Event-Driven	0.84	0.57
Equity Hedge	0.89	0.54
Global Macro	0.82	0.17
Relative Value	0.65	0.61

Table 1.3 – Main statistics of the HFR indexes (net of fees). *Note: Calmar ratio is the ratio of the annual return to the maximum drawdown (MDD).*

	Ann. Ret. (in %)	Ann. Vol. (in %)	Sharpe Ratio ( $r_f = 0\%$ )	VaR (95%) (in %)	MDD (in %)	Calmar Ratio
Eq. Market Neut.	2.86	2.46	1.17	1.10	-5.82	0.49
Eq. Quant. Dir.	4.06	6.68	0.61	2.92	-12.75	0.32
Eq. Short Selling	-8.74	9.86	-0.89	4.68	-49.31	-0.18
Fund of funds	2.45	3.78	0.65	1.80	-6.98	0.35
Systematic Div.	2.23	7.36	0.30	3.32	-11.27	0.20
Convertible Arb.	4.27	4.46	0.96	2.33	-8.96	0.48
F.I. Multistrat.	4.77	3.25	1.47	1.64	-4.57	1.04
Event-Driven	4.08	5.44	0.75	2.61	-10.37	0.39
Equity Hedge	3.62	7.60	0.48	3.74	-12.88	0.28
Global Macro	1.43	4.46	0.32	2.14	-7.85	0.18
Relative Value	5.11	3.31	1.55	1.66	-5.62	0.91

Table 1.4 – Summary statistics of all TREND factors’ monthly returns, on the periods running from January 2010 to March 2016 (FH period), from December 1993 to July 2017 (Whole period), from December 1993 to March 2009 (Before GFC) and from April 2009 to July 2017 (After GFC).

FH Period												
	TREND	TRENDCOM	TRENDSTK	TRENDBD	TRENDEX	TRENDIM	TREND3M	TREND6M	TREND2Y	TRENDST	TRENDLT	
Mean (in %)	0.85	0.83	0.10	0.85	0.35	0.15	0.46	0.55	0.87	0.91	0.88	
Std. Dev (in %)	2.72	3.31	2.29	2.99	3.08	2.63	2.58	2.74	2.87	3.04	2.69	
Q25 (in %)	-0.81	-1.40	-1.23	-1.27	-1.61	-1.54	-1.32	-1.19	-0.97	-0.92	-1.46	
Median (in %)	0.53	0.97	-0.42	0.33	-0.08	0.11	0.62	0.70	0.39	0.81	0.78	
Q3 (in %)	2.73	2.24	1.25	2.20	1.66	2.02	1.96	2.50	2.98	2.80	2.44	
Skewness	0.27	0.47	0.41	1.05	0.94	0.10	0.15	-0.15	0.03	-0.03	0.39	
Kurtosis	2.80	3.32	2.78	3.91	4.14	2.81	3.09	2.89	2.86	2.77	2.96	
Whole Period												
	TREND	TRENDCOM	TRENDSTK	TRENDBD	TRENDEX	TRENDIM	TREND3M	TREND6M	TREND2Y	TRENDST	TRENDLT	
Mean (in %)	0.98	0.66	0.49	0.82	0.44	0.65	0.66	0.71	0.95	0.67	0.74	
Std. Dev (in %)	2.91	3.23	2.79	3.08	2.79	2.69	2.84	2.88	2.83	2.82	2.81	
Q25 (in %)	-0.86	-1.39	-1.16	-1.24	-1.44	-1.19	-1.31	-1.21	-0.91	-1.04	-1.10	
Median (in %)	0.66	0.32	-0.01	0.33	0.12	0.37	0.44	0.63	0.75	0.56	0.37	
Q3 (in %)	2.65	2.21	1.57	2.13	1.89	2.13	2.11	2.52	2.81	2.39	2.16	
Skewness	0.79	1.05	1.02	0.87	0.98	0.91	1.13	0.36	0.21	0.02	1.47	
Kurtosis	4.95	7.63	5.11	4.05	4.88	5.73	7.32	4.37	3.25	3.17	8.59	
Before GFC												
	TREND	TRENDCOM	TRENDSTK	TRENDBD	TRENDEX	TRENDIM	TREND3M	TREND6M	TREND2Y	TRENDST	TRENDLT	
Mean (in %)	1.15	0.75	0.65	0.89	0.56	0.94	0.76	0.79	1.10	0.72	0.96	
Std. Dev (in %)	3.03	3.29	3.04	3.14	2.77	2.74	3.01	2.98	2.85	2.75	2.96	
Q25 (in %)	-0.72	-1.22	-0.98	-1.16	-1.34	-1.00	-1.30	-1.17	-0.79	-0.94	-0.97	
Median (in %)	0.77	0.33	0.02	0.38	0.27	0.51	0.44	0.58	1.21	0.54	0.42	
Q3 (in %)	2.74	2.33	1.65	2.28	2.02	2.51	2.28	2.58	2.81	2.44	2.49	
Skewness	0.88	1.18	1.01	0.73	0.96	1.13	1.32	0.50	0.24	0.03	1.63	
Kurtosis	2.80	3.32	2.78	3.91	4.14	2.81	3.09	2.89	2.86	2.77	2.96	
After GFC												
	TREND	TRENDCOM	TRENDSTK	TRENDBD	TRENDEX	TRENDIM	TREND3M	TREND6M	TREND2Y	TRENDST	TRENDLT	
Mean (in %)	0.60	0.46	0.15	0.66	0.18	0.02	0.43	0.51	0.60	0.55	0.26	
Std. Dev (in %)	2.60	3.08	2.11	2.97	2.82	2.48	2.43	2.64	2.78	2.98	2.38	
Q25 (in %)	-1.03	-1.55	-1.20	-1.30	-1.61	-1.72	-1.31	-1.22	-1.12	-1.30	-1.35	
Median (in %)	0.45	0.29	-0.05	0.14	-0.15	0.07	0.50	0.71	0.28	0.72	0.02	
Q3 (in %)	1.90	2.03	1.31	1.99	1.21	1.44	2.01	2.36	2.45	2.23	1.72	
Skewness	0.33	0.64	0.36	1.20	1.04	0.21	0.14	-0.14	0.12	-0.00	0.48	
Kurtosis	2.93	3.73	3.00	4.62	4.81	2.99	3.16	2.83	3.05	2.81	3.21	

Figure 1.3 – Track record of our TREND factor. *Note: Log prices are displayed.*



Table 1.4 exhibits the statistics of the factors over several periods. TREND factor on average earns 0.85% per month during the period running from January 2010 to March 2016 with a 2.72% monthly standard deviation. Over the full sample, the average monthly return is 0.98%, close to the sub-sample value. The other distribution metrics are similar as well, suggesting the sub-period is similar to the full one in terms of the trend factor returns. Average monthly return decreases from 1.15% in the pre-GFC period to 0.60% post-GFC, being almost divided twofold.

As we can see on Figure 1.3, we notice good performances during the GFC, which allows to maintain our factor as a potential candidate for understanding the performances of that period.

Table 1.5 shows the main performance and risk measures of TREND fac-

Table 1.5 – Main statistics of our monthly TREND factors (gross of fees) over the global period. *Note: (1) is TREND, (2) is TRENDCOM, (3) is TRENSTK, (3) is TRENDBD, (4) is TRENDFX, (5) is TRENDST and (6) is TRENDLT. Calmar ratio is the ratio of the annual return to the maximum drawdown (MDD).*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Ann. Ret. (in %)	11.62	7.65	6.01	9.78	4.97	8.81	10.43
Ann. Vol. (in %)	9.98	11.08	9.71	10.54	9.65	9.68	9.71
Sharpe Ratio ( $r_f = 0\%$ )	1.16	0.69	0.62	0.93	0.52	0.91	1.07
VaR (95%, in %)	1.16	0.69	0.62	0.93	0.52	0.91	1.07
MDD (in %)	-10.33	-21.47	-13.81	-13.24	-16.47	-11.41	-13.01
Calmar Ratio	1.12	0.36	0.44	0.74	0.30	0.77	0.80

tors. As said before, volatility is a parameter which can be fixed at whatever level without loss of generality, so here we set it at 10% annual daily volatility for comparison purposes.<sup>6</sup> The global TREND factor exhibits Sharpe and Calmar ratios slightly higher than 1, which is similar to the results on time-series momentum factors from MOP (2012) [82] and BK (2012) [17]. When decomposing this factor into the four *sector*-TREND factors, the risk-adjusted performances are lower and vary depending on the traded asset class. For example, TRENDCOM and TRENDFX suffer from large drawdowns, whereas TRENDBD has statistics closer to the full version ones. Tables A1 and A2 in Appendix contain the performance statistics for all factors, including the ones built on one lookback. Though with a lower dispersion, same conclusions can apply when decomposing TREND by signal horizon: Calmar Ratio varies from 0.42 to 0.96. The most-performing factor is the one with a 1-year momentum, confirming the findings of Hurst, Ooi and Pedersen (2013) [57].

Table A3 in Appendix presents the correlations of all our TREND factors with Fung and Hsieh factors. Concerning the standard asset class benchmarks, correlations with TREND are close to zero except for the 10 Year

6. Performances of our factor are gross of fees (management, performance and expense fees) as well as gross of transaction costs.

T-Bond. Indeed, the steady decrease in the US rates due to the quantitative easing by the U.S. Federal Reserve Bank (FED) made trend followers maintain their position during the whole period, thus explaining the relatively high correlation with bonds. As for the PTFS option factors, correlations evolve between 0.18 for PTFSCOM to 0.51 for PTFSEFX. This confirms the work of Fung and Hsieh, their lookback straddle portfolios capturing part of the variation due to a trend exposure. Unsurprisingly, the correlation between the *sector*-TREND factors and the PTFS factors are lower on average, with the highest correlation often reached when the asset class is the same. For example, TRENDFX has a 0.59 correlation with PTFSEFX. However, TRENDCOM exhibits a 0.31 correlation with PTFSEFX, whereas its correlation with PTFSCOM is 0.29. Still, these intra-asset class correlations between Fung and Hsieh and our specifications remain quite low. Let's now look at the relations between Fung and Hsieh factors and the signal horizon. For each asset class, the correlation decreases when the horizon of our factor increases. For instance, PTFSEBD has a 0.5 correlation with TREND1M, 0.38 with TREND3M and a very low 0.09 correlation with TREND2Y. In their construction, Fung and Hsieh (2001) [46] use options with quarterly expirations, thus capturing trends over this timeframe. A momentum signal with a lookback inferior to three months is needed to capture such trends, confirming the previous finding. As a robustness check, correlations were also calculated for the factors built on a selection of six futures and results were not economically different (refer to Table A8 in Appendix).

As we can see on Table A4 in Appendix, correlations are relatively low between TREND and the HFR indexes, except for Global Macro and Systematic Diversified, and Fund of Funds to a lower extent. The pattern is very similar for both TRENDCOM and TRENDFX factors. TRENDSTK correlations are high with all hedge funds indexes except for Equity Short Selling, suggesting trends on this asset class are essentially long since hedge

funds are usually positively exposed to the equity risk premium, even for the Equity Market Neutral style. TRENDDBD is positively correlated to both Systematic Diversified and Global Macro, but relations with other styles are in opposite direction as the ones of the TRENDSTK factor. In addition, TRENDSTK and TRENDDBD are negatively correlated, with -0.17 correlation. Despite the quantitative easing, which results in upward trends in both rates and equities, there is still dispersion in the trends in these asset classes. In terms of lookback horizon of the signals, six month and one year display the largest correlation to the two directional strategies that are Systematic Diversified and Global Macro. All these findings are encouraging, but need to be checked for robustness. To do so, we need to adjust the correlation by the other known risk factors, by calculating the beta on our factor in a multivariate regression. This is the goal of the following section.

## 1.4 Hedge funds exposure

We start with the time-series analysis of returns of hedge funds indices, and examine their exposure on our TREND factor. Our benchmark model is the standard Fung and Hsieh (2001) [46] nine-factor model. A hedge fund series of excess returns  $r_{i,t}$  can be decomposed into a risk-adjusted performance,  $\alpha_i$ , and a systematic performance coming from the exposures  $\beta_i^k$  to the  $k$  factors. The unexplained variation is the residuals  $\epsilon_i$ , that are supposed to follow a normal distribution in the Ordinary Least Squares model.

### 1.4.1 Trends everywhere?

In order to understand the relation between the hedge fund indices and trends, we add our TREND factor to the model, making a 10-factor risk model:

$$\begin{aligned} r_{i,t} = & \alpha_i + \beta_i^1 \text{Equity} + \beta_i^2 \text{Size} + \beta_i^3 \text{Bond} + \beta_i^4 \text{Credit} + \beta_i^5 \text{PTFSBD} \\ & + \beta_i^6 \text{PTFSFX} + \beta_i^7 \text{PTFSCOM} + \beta_i^8 \text{PTFSIR} \\ & + \beta_i^9 \text{PTFSSTK} + \beta_i^{10} \text{TREND} + \epsilon_i \quad (1.8) \end{aligned}$$

where  $r_{i,t}$  denotes the monthly return of the hedge fund index  $i$  in excess of the 3-month Euribor, and the regressors are described in the data section.

We want to test whether our factor improves the understanding of the two directional "macro" strategies, as represented by the Systematic Diversified and Global Macro indexes. If the beta on our factor is significant and the R-squared increases (in comparison to the nine-factor model, without TREND), we can conclude that our trend following specification contains something related to the macro strategies than is not present in the Fung-Hsieh factors. If not, it means that trends harvested as in our specification are either the same as the ones with lookback straddles or that the macro strategies do not capture them.

Results presented in Table 1.6 show that our factor greatly improves the understanding of the Systematic Diversified index, with a 0.80 beta associated with a t-statistic of 12.30. The R-squared increases from 38% for the benchmark model to 82% for the full model. Thus, we can conclude the Systematic Diversified index contains trend following, as implemented in our construction.

Table 1.6 also presents the results of the factor model for the Global Macro index. Again, the beta is highly significant (t-statistic of 11.43) and the R-squared drastically increases from 37% to 79%. We can conclude the Global Macro index returns are related to trend following ones.<sup>7</sup>

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7. We also modify the specification of Equation (8) to compare the results we obtain when we replace in this equation the TREND factor by the cross-sectional equity momen-

Table 1.6 – Regressions of Systematic Diversified and Global Macro indexes on the Fung-Hsieh factors, combined with our TREND factor for both specifications (with and without TREND). T-statistic is displayed below the coefficients. *Note: Significant variables are in bold.*

	Systematic Diversified		Global Macro	
	(With TREND)	(Without TREND)	(With TREND)	(Without TREND)
Alpha	<b>-0.60%</b> <b>(-3.60)</b>	0.09% (0.30)	<b>-0.40%</b> <b>(-3.71)</b>	0.02% (0.09)
Equity	<b>0.16</b> <b>(4.30)</b>	<b>0.24</b> <b>(3.43)</b>	<b>0.15</b> <b>(6.08)</b>	<b>0.20</b> <b>(4.59)</b>
Size	-0.08 (-1.38)	-0.16e (-1.56)	-0.02 (-0.44)	-0.07 (-1.05)
Bond	-0.02 (-1.31)	-0.04 (-1.14)	-0.01 (-0.68)	-0.02 (-0.83)
Credit	0.01 (0.36)	-0.05 (-0.88)	0.00 (0.11)	-0.03 (-1.00)
PTFSBD	0.01 (0.59)	0.03 (1.94)	-0.00 (-0.44)	0.01 (1.35)
PTFSFX	0.01 (1.54)	<b>0.05</b> <b>(3.84)</b>	0.01 (1.14)	<b>0.03</b> <b>(3.57)</b>
PTFSCOM	0.01 (1.26)	0.01 (0.86)	0.00 (0.33)	0.00 (0.38)
PTFSIR	0.00 (0.44)	0.01 (0.33)	0.00 (0.80)	0.01 (0.56)
PTFSSTK	<b>-0.02</b> <b>(-2.97)</b>	-0.02 (-1.14)	<b>-0.01</b> <b>(-2.76)</b>	-0.01 (-1.18)
TREND	<b>0.80</b> <b>(12.30)</b>		<b>0.48</b> <b>(11.43)</b>	
$R^2$	0.82	0.38	0.79	0.37

As expected, Systematic Diversified and Global Macro strategies are exposed to this trend-following strategy. The first is systematic and both are invested across asset classes, and these features also correspond to our factor. However, exposures to different asset classes could have been captured thanks to the factors in the benchmark model. Indeed, the major equity and fixed income benchmarks are present as well as systematic portfolios of options, also written on currencies and commodities. We can then conclude a significant exposure on TREND is not simply the result of a cross-asset

tum factor (WML). We obtain evidence that the TREND factor brings something else than the standard WML. The same conclusion occurs when we include both WML and TREND in the specification. All these results are available upon request.



dimension but is truly an indicator of an exposure to trends.

The natural question that comes up has to do with the hedge fund strategies that are not cross-asset in essence. For example, could a long/short equity portfolio be in fact exposed to macro trends despite investing only on cash equities? The same question applies to the other alternative strategies. To answer this question, we apply our ten-factor model to the rest of the alternative space. Again, a significant and positive beta indicates the presence of a trend strategy in the analyzed index. By definition, Multi-Strategy and Fund of Funds are strong candidates to have an exposure on TREND, since they invest internally or externally in a set of alternative strategies. The rest of the strategies often aim at capturing a given fundamental premium on an asset class, resulting in different positions than the momentum ones. Results of the regressions can be found in Table A5 in Appendix.

Fund of funds index displays a positive beta with a t-statistic of 4.88, confirming these funds allocate part of their capital to diversified trend following strategies. Surprisingly, the Equity Hedge Quantitative Directional exhibits a low positive beta but significant at a 5% level (t-statistic of 2.18). Indeed, some statistical arbitrage strategies present in this index might position themselves according to past price momentum, since such phenomenon has been shown to be significant in some markets. All remaining HFR indexes do not exhibit a significant loading on TREND, confirming their focus on one asset class and a different premium than momentum.

### 1.4.2 Asset Class-Trends everywhere?

We now want to dig deeper into the hedge fund styles, and a way to do that is to use the decomposition feature of our construction and replace our TREND factor by its four *sector*-TREND components. We want to test whether some strategies exhibit an exposure to trends in specific asset classes. To do so, we use again a factor model, where the TREND factor is

replaced by four asset class TREND components: TRENDSTK, TRENDDBD, TRENDFX and TRENDCOM. We split the test into two parts, depending on the previous results. For the alternative indexes that do not show any exposure on the macro level, we test if they are not at all exposed to any trends or if they do on the sector level but the exposure gets erased during the aggregation step of the construction, where some diversification comes into play. Secondly, for the ones that show an exposure to the global TREND factor, we test if this exposure comes from all asset classes or if it is related to a specific one.

Table 1.7 – Regressions of the HFR indexes on the Fung-Hsieh factors, combined with the four sector TREND factors. T-statistic is displayed below the coefficients. *Note: Only sector TREND factors are displayed but the model used is the full one, with Fung-Hsieh nine factors.*

	TRENDCOM	TRENDSTK	TRENDDBD	TRENDFX	$R^2$
Equity Market Neutral	-0.01 (-0.17)	-0.07 (-1.57)	0.08 (1.23)	0.09 (1.54)	0.72
Equity Quant. Directional	0.01 (0.09)	0.05 (0.63)	0.1 (0.93)	0.14 (1.45)	0.90
Equity Short Selling	0.18 (0.79)	-0.19 (-1.33)	0.25 (1.24)	-0.21 (-1.13)	0.84
Fund of funds	0.09 (0.9)	<b>0.26</b> <b>(4.47)</b>	0.05 (0.57)	0.12 (1.6)	0.81
Systematic Diversified	<b>0.89</b> <b>(4.94)</b>	<b>0.66</b> <b>(6.01)</b>	<b>0.59</b> <b>(3.74)</b>	<b>0.37</b> <b>(2.61)</b>	0.82
Convertible Arbitrage	0.24 (1.61)	0.02 (0.27)	-0.04 (-0.32)	-0.13 (-1.1)	0.66
Fixed Income Multistrat.	0.09 (0.85)	<b>0.17</b> <b>(2.52)</b>	0.02 (0.24)	-0.11 (-1.29)	0.67
Event-Driven	-0.09 (-0.69)	0.14 (1.76)	-0.05 (-0.43)	-0.01 (-0.06)	0.82
Equity Hedge	0.03 (0.2)	0.09 (1.05)	-0.03 (-0.22)	-0.09 (-0.78)	0.89
Global Macro	<b>0.57</b> <b>(4.87)</b>	<b>0.39</b> <b>(5.48)</b>	<b>0.37</b> <b>(3.66)</b>	<b>0.19</b> <b>(2.04)</b>	0.80
Relative Value	-0.07 (-0.65)	0.09 (1.38)	0.07 (0.82)	-0.07 (-0.87)	0.71

As we can see on Table 1.7, the Systematic Diversified index exhibits positive and significant exposures across all *sector*-TRENDS, Equities being the strongest and Currencies the weakest. The result is similar for the Global

Macro index with slightly lower t-statistics. We know the significant exposure at a macro level for these strategies does not necessarily come from their cross-asset dimension, since Fung-Hsieh factors are here to control for that, but in addition we know they are harvesting trends everywhere. Fund of Funds index exhibited a high exposure to TREND and we interpreted that as a capital allocation to trend followers, which should result in an exposure to TREND across asset classes, as per the results on the Systematic Diversified style. Unexpectedly, beta is only significant to TRENDSTK. Fund of Funds allocate capital between many strategies and diversify between managers among each of them. Recall that any long-only static exposure has been controlled for with Fung and Hsieh factors. A possibility is that there is capital invested in strategies with opposite positions on these asset classes, thus reducing the net exposure we observe. For example, contrarian strategies such as mean reverting might be exploited on commodities. The Equity Hedge Quantitative Directional low but significant macro exposure disappears when zooming into asset classes.

Finally, among the strategies not showing a global TREND exposure, none exhibits an asset class specific TREND exposure. Inversely, among the ones that exhibited a global TREND exposure, all show significant results across asset classes except the Fund of Funds index. The trends harvested on the macro level are the same trends that can be harvested per asset class.

### 1.4.3 Horizon-Trends everywhere?

Apart from the traded futures markets and thus the asset classes, another major parameter is the horizon over which trends are detected. Relying on the past month or the past year' prices results in an important difference in position. As explained in the methodology, our trend signal is the simple average of five momentums (each with a specific timeframe) and we showed the TREND can be linearly decomposed into *horizon*-Trend factors, noted

TREND1M, TREND3M, TREND6M, TREND1Y and TREND2Y. First, we want to test whether Systematic Diversified and Macro styles are exposed to all types of trends or specific ones. Second, we want to check if there is some exposure on specific trends for the strategies that did not exhibit any Trend exposure on the macro level as well as the asset class. We will rely on the t-statistics per factor to conclude.

Table 1.8 – Regressions of the HFR indexes on the Fung-Hsieh factors, combined with the five horizon TREND. T-statistic is displayed below the coefficients. *Note: Only horizon TREND factors are displayed but the model used is the full one, with Fung-Hsieh nine factors.*

	TREND1M	TREND3M	TREND6M	TREND1Y	TREND2Y	$R^2$
Eq. Market Neut.	-0.05 (-0.76)	-0.07 (-0.91)	-0.1 (-1.37)	<b>0.16</b> <b>(2.4)</b>	0.11 (1.93)	0.76
Eq. Quant. Dir.	0.01 (0.1)	0.06 (0.45)	-0.08 (-0.6)	0.06 (0.52)	<b>0.25</b> <b>(2.63)</b>	0.91
Eq. Short Selling	-0.26 (-1.14)	-0.37 (-1.47)	0.19 (0.77)	-0.02 (-0.1)	0.12 (0.66)	0.84
Fund of funds	0.16 (1.63)	0.18 (1.66)	-0.03 (-0.28)	0.11 (1.23)	<b>0.18</b> <b>(2.27)</b>	0.80
Systematic Div.	<b>0.37</b> <b>(2.29)</b>	<b>0.86</b> <b>(4.71)</b>	0.26 (1.48)	<b>0.78</b> <b>(5.02)</b>	0.13 (0.98)	0.85
Convertible Arb.	0.18 (1.22)	0.21 (1.26)	-0.27 (-1.69)	-0.05 (-0.34)	0.11 (0.94)	0.67
Fixed Inc. Mult.	0.13 (1.23)	0.19 (1.57)	-0.12 (-1.02)	0.01 (0.06)	0.02 (0.2)	0.65
Event-Driven	0.14 (1.1)	0.14 (0.96)	-0.22 (-1.53)	-0.05 (-0.36)	0.13 (1.24)	0.82
Equity Hedge	0.08 (0.55)	0.27 (1.74)	<b>-0.34</b> <b>(-2.27)</b>	-0.13 (-0.99)	<b>0.24</b> <b>(2.07)</b>	0.90
Global Macro	<b>0.29</b> <b>(2.61)</b>	<b>0.51</b> <b>(4.01)</b>	0.11 (0.91)	<b>0.40</b> <b>(3.67)</b>	0.17 (1.81)	0.81
Relative Value	0.11 (1.15)	0.17 (1.54)	<b>-0.23</b> <b>(-2.16)</b>	-0.07 (-0.71)	0.13 (1.56)	0.73

Table 1.8 tells us six months (TREND6M) and two-years trends (TREND2Y) are not significant for both the Systematic Diversified and the Macro styles. Three-months and one-year trends seem to be the horizon most present in these strategies. Assuming the portfolio managers are doing a good job, thus positioning themselves on the most lucrative horizon, this confirms the finding of Moskowitz, Ooi and Pedersen (2012) [82] who show

the autocorrelation of risk-adjusted returns is the highest around 260 days. Across the non-directional strategies, we can find some statistically significant betas (with t-statistic just above 2). Surprisingly, Equity Hedge and Relative Value indexes exhibit a negative loading on the 6 months-Trends. T-statistics are higher than 2 but not enough for a 1% significance, which points toward a statistical artifact rather than a true short exposure. However, there are no strong economically meaningful exposures in the space apart from Systematic Diversified and Macro styles.

## 1.5 Cross-sectional analysis

In this section, we perform a sort of "out-of-sample" analysis since we move on to individual hedge fund data. We do so to examine the relationship between TREND returns and hedge funds returns. First, we form portfolios of hedge funds based on their rolling beta to our factor and we analyze the difference in return between the opposite portfolios being the low beta portfolio and the high beta one. Secondly, we regress the overall beta of the funds against either their overall annual return or their maximum drawdown, after controlling for fund level characteristics such as fees.

Table 1.9 – Summary statistics of the EuroHedge database (N=1685 funds). *Note: P25 is the 25% percentile, or Q1. Similarly, P75 is the 75% percentile, or Q3.*

Fund Characteristic	Mean	Std. Dev.	P25	Median	P75
Return (% per month)	0.34	0.34	0.11	0.27	0.49
Mgt. Fee (in %)	1.46	1.13	1.00	1.50	2.00
Incentive Fee (in %)	16.98	7.04	15.00	20.00	20.00
Age (years)	8.14	4.67	4.33	8.00	11.84
AUM (US\$M)	1 454.66	4 335.61	30.00	179.93	792.00

Before analyzing the relationship between trend exposure and returns, Table 1.9 displays distribution statistics of hedge funds characteristics. The sample covers all funds from 2000 to end of 2017. Despite the presence of

the GFC in the period, the average mean monthly return is 0.34%, which is equivalent to an average of 4.16% per year. However, median age of the funds is 8 years, meaning that at least half of the funds were not alive in 2008. Another interesting fact is the large difference between mean and median AUM, pointing toward a right-skewed distribution, with few very large funds. In terms of fees, hedge fund investing is getting cheaper, with a mean management fee of 1.46% and a mean incentive fee of 16.98%. However, around 25% of the funds still charge the standard 2/20 structure. Note that the fees reported in the EuroHedge database are relative to a share of a fund and not to the whole asset management company, and often for the most expensive share, so the actual AUM-weighted fee might be lower.

### 1.5.1 Are trends priced?

We start by exploring whether the differences in funds' TREND exposure can explain the cross-sectional differences in their performances. On a 36-months rolling basis, we estimate the following linear regression:

$$r_{i,t} = \alpha_{i,t} + \beta_{i,t} \text{TREND}_t + \epsilon_{i,t} \quad (1.9)$$

where  $r_{i,t}$  denotes the volatility-adjusted returns of the fund  $i$  over the 36-months window,  $\text{TREND}_t$  the returns of our factor over the same period. Here, both series of returns have the same volatility, in order not to detect an increase in the fund volatility as an increase in the Trend exposure and to be able to compare funds between them.

The objective is to detect if this assertion (or the opposite) is true: the bigger the TREND exposure of the fund, the bigger the return. A nonparametric way to test it is to form portfolios of funds with different betas. The obtained portfolios will exhibit a beta to TREND close to its components' betas. At each date  $t$ , we split the available pool of funds into four groups,

corresponding to the four quartiles of betas, and we compute the average return of each group, thus forming a portfolio. Quartile 1 (4) portfolio contains funds with the lowest (highest) TREND exposure.

Table 1.10 – Quantile portfolios statistics (based on univariate  $\beta_{TREND}$  sorts). T-statistic is displayed below the coefficients. Results concern the period starting in January 2010 ending in March 2016. *Note: Funds have been scaled to have the same volatility as TREND, on each window.*

	QUANTILE PORTFOLIOS		
	1 (LOW)	4 (HIGH)	4 - 1
Ann. Return (in %)	11.44 (5.52)	7.72 (3.10)	-3.72
9-factor Alpha (in %)	0.15 (0.88)	0.56 (2.19)	0.41
Avg. $\beta_{TREND}$	-0.29	0.44	

Table 1.10 reports average TREND beta, annual return and 9-factor alphas of TREND beta sorted quantiles portfolios. The portfolio composed of funds with low TREND beta, noted 1 (LOW), performs better than its high beta counterpart, with an annual return of 11.44% against 7.72%. However, this specification does not allow to control the first-order effect, which is the type of strategy. Indeed, it is highly probable we extracted most of the Managed Futures funds via the high beta portfolio. Risk-adjusted returns are the other way around: the high TREND beta portfolio delivers a significant alpha of 56 basis points per month, versus a non-significant 15 basis points for the low TREND beta portfolio. Nevertheless, these results are model-dependant, in other words we cannot be sure the strategy style is properly controlled when adding the other risk factors.

This indicates a strong positive link between TREND exposure and the risk-adjusted fund performance. However, the quartile portfolios are equal-weight baskets of funds which might have very different characteristics such as other risk exposures or even fund characteristics, resulting in two quartiles that do not differ only by the TREND exposure degree of freedom. In other words, the TREND beta is linked to other betas. A way to control for the

strategy style is to stay at the fund level, where this information is available, and that is the objective of the following section.

### 1.5.2 Individual funds classification

In this section, we estimate the reward associated to the TREND risk factor. The first step consists in a time-series estimation of the overall beta of each fund on the factor:

$$r_{i,t} = \alpha_i + \beta_i^{TREND} \text{TREND}_t + \epsilon_{i,t} \quad (1.10)$$

where  $r_{i,t}$  denotes the returns of fund  $i$ ,  $\text{TREND}_t$  the returns of the TREND factor.

The second-step is cross-sectional and consists in regressing the annual performance or the maximum drawdown of each fund against its beta, as well as fund characteristics. Specifically, in the first specification, we estimate the following OLS model:

$$\begin{aligned} R_{fund} = & \alpha + \lambda_{\beta^{TREND}} \beta^{TREND} + \lambda_{MngtFee} * MngtFee \\ & + \lambda_{IncFee} * IncFee + \lambda_{Age} * Age + \epsilon \end{aligned} \quad (1.11)$$

where  $R_{fund}$  denotes the series of annual returns across funds,  $\beta^{TREND}$  is the beta estimated in the first step,  $MngtFee$  and  $IncFee$  describe the fee structure, and  $Age$  is the number of years since inception as of 31/12/2017. Equation 1.11 is the full specification, where the premium  $\lambda_{\beta^{TREND}}$  is risk-adjusted in the sense other risk factors known to drive difference in hedge funds performance are put as covariates. All things equal,  $\lambda_{\beta^{TREND}}$  is the sensitivity of the overall annual performance of the fund to the value of its  $\beta^{TREND}$ . So, a positive and significant coefficient will act as evidence for a



trend following reward.

In the remaining part of this section, we split the sample of hedge funds into two sub-samples: funds which are not in the Managed Futures Category, and Managed Futures funds. Table 1.11 shows the distribution metrics of the funds' characteristics, for each subsample: outside versus inside the Managed Futures category. Systematic Diversified Index is the HFR index that has the largest exposure to TREND, so it is expected individual funds exhibit the same behavior. As expected,  $\beta^{TREND}$  is higher on average for Managed Futures than for other hedge funds, 0.26 versus -0.01. The Welch test for the mean difference gives a t-statistic of 12.61. Ex-MF hedge funds earn more than Managed Futures on average, and this stays true for different levels of quantiles. Despite not being adjusted by firm characteristics, this is consistent with the negative premium observed in the non-parametric test. As for the rest of the fund characteristics, no significant difference can be observed.

Table 1.11 – Statistics of the subsamples: ex-MF funds (N=852) and Managed Futures funds (N=106). *Note: The subset contains hedge funds which met the following criteria: at least 20\$M and 2 years of track record.*

Hedge Funds ex-MF					
	$\beta_{TREND}$	Ann. Ret.	Mgmt Fee	Incentive Fee	Age (in years)
Mean	-0.01	9.08%	1.45%	16.51%	9.26
Q1	-0.06	5.25%	1.00%	15.00%	5.50
Median	-0.01	7.87%	1.50%	20.00%	9.16
Q3	0.03	11.32%	2.00%	20.00%	12.67
Managed Futures					
	$\beta_{TREND}$	Ann. Ret.	Mgmt Fee	Incentive Fee	Age (in years)
Mean	0.26	7.00%	1.42%	18.94%	8.91
Q1	0.05	3.04%	1.00%	20.00%	4.43
Median	0.23	6.07%	1.83%	20.00%	7.92
Q3	0.42	9.87%	2.00%	20.00%	13.71

### Among Managed Futures

We first focus on the subsample of the Managed Futures funds and Table 1.12 displays the results of both regression models. For both annual return and drawdown risk, there is little explanatory power of the TREND beta. Indeed, R-squared are quite small (especially for the first specification) and t-statistics are lower than 2, indicating non-significant loadings. The differentiation due to TREND exposure is more difficult to see in the Managed Futures space since all funds exploit to some extent the time-series momentum strategy, thus reducing the potential variance to explain. There are conflicting interpretations that make sense. One could argue that Managed Futures funds exposed to the TREND factor are actually using a sub-optimal strategy and could be tagged as "beta funds", whereas Managed Futures funds with a low beta to TREND are using a more sophisticated strategy, and could be tagged as "alpha funds". Assuming the Managed Futures space is not that homogeneous, exposure to TREND could just disentangle trend following funds from funds pursuing other types of strategy (pattern recognition, commodity seasonalities, mean reversion...), without any view on the trend strategy 'quality'.

Table 1.12 – Cross-sectional regressions of Overall Annual Return and Maximum Drawdown. *Note: Specification 1 contains only the TREND beta as a regressor, whereas the specification 2 is the full one. The model was applied on a subset of 373 hedge funds which met the following criteria: in the Managed Futures category, at least 200\$M and 4 years of track record.*

	$y = \text{Annual return}$		$y = \text{MDD}$	
	1	2	1	2
$\beta_{TREND}$	2.24%	1.26%	0.37%	0.22%
	(0.83)	(0.49)	(0.99)	(0.63)
Age		0.27		0.04
		(2.14)		(2.31)
Alpha	6.18%	3.49%	1.47%	1.07%
	(5.67)	(2.15)	(9.83)	(4.87)
$R^2$	2.1%	14.7%	3.0%	17.2%

**Among Hedge Funds ex-Managed Futures**

Table 1.13 displays the results of the cross-sectional regression, respectively of the overall annual return and the maximum drawdown. In both specifications of the overall return regression,  $\lambda_{\beta TREND}$  is negative, meaning that on average, a higher exposure to TREND (1 point) is associated to a lower return (-7%). Hedge Funds which are not in the Managed Futures space bear a cost for being exposed to TREND, our proxy for the trend-following strategy. This is consistent with the idea this strategy is a protection in times of crisis, and resembles an insurance. As with all insurances, there is a cost, generally called the premium. Our result is consistent with the observation that on the long run, trend following funds display a lower Sharpe Ratio than other strategies, more related to arbitrage such as Relative Value.

Table 1.13 – Cross-sectional regressions of Overall Annual Return and Maximum Drawdown. *Note: Specification 1 contains only the TREND beta as a regressor, whereas the specification 2 is the full one. The model was applied on a subset of 373 hedge funds which met the following criteria: at least 200\$M and 4 years of track record.*

	$y = \text{Annual return}$		$y = \text{MDD}$	
	1	2	1	2
$\beta_{TREND}$	-7.31% (-3.46)	-7.35% (-3.52)	66.62% (7.53)	66.83% (8.21)
Age		0.17 (3.10)		-1.79 (-8.21)
Alpha	8.58% (38.79)	6.78% (10.94)	-20.50% (-21.77)	-1.62% (-0.66)
$R^2$	3.2%	5.6%	13.4%	26.9%

The counterpart of bearing this insurance cost is the reward in times of crisis. We modelled it as a potential reduction of a drawdown-based risk measure. Indeed, funds more exposed to TREND exhibit on average lower drawdowns.

In terms of business economics, our results indicate that funds outside the Managed Futures space exposed to TREND are doing a suboptimal allo-

cation, assuming this exposure is by choice. Indeed, protection against crisis can be attained through different mechanisms: global leverage, beta timing in case of equity funds, options buying and all these correlate to trend following at some point. However, these insurances seem to be more costly than the pure trend insurance offered by Managed Futures funds. The optimal choice would be to externalize this protection function to specialized funds. A natural extension would be to reproduce the same exercise on Long/Short Equity funds, that is explaining their returns with our equity-only TREND-STK factor. That way, we would be able to detect if they are timing their global beta and to assess if this dynamic hedge is costly. Isn't it better to externalize and keep a market neutral portfolio with an overlay of TREND-STK rather than trying to time the beta on their own as some L/S equity funds do?

## 1.6 Robustness checks

### 1.6.1 Factor construction

In order to check the contribution of our factor, we run the HFR indexes regressions with TREND replaced by its equity-only version, TRENDSTK. This factor trades 12 futures indices. For all specifications, as we can see on Table 1.14, results are worse than with the full version TREND, with lower R-squared, and lower t-statistics. Indeed, the t-statistics are between 3 and 4, comparing to 11 in the standard case. R-squared only reaches 56% in the most complete specification (4), compared to 72% before.

As Table 1.15 shows, results are similar (even larger R-squared reductions) for the other sub-versions of TREND, built on only one asset class. Indeed, selecting futures of a particular asset class (then using a non-diversified Trend index) greatly reduces the explanatory power of the model. That confirms a big part of our contribution lies in the diversified feature of our factor.

Table 1.14 – Regressions of Global Macro (GM) and CTA indexes on the Fung-Hsieh factors, combined with our TRENDSTK factor. T-statistic is displayed below the coefficients.

	(1)		(2)		(3)		(4)	
	GM	CTA	GM	CTA	GM	CTA	GM	CTA
Alpha	0.08%	0.13%	0.02%	0.17%	-0.04%	0.03%	0.00%	0.06%
	(0.57)	(0.55)	(0.15)	(0.72)	(-0.26)	(0.12)	(0.03)	(0.26)
Equity			0.08	-0.05	0.09	0.03	0.11	0.09
			<b>(2.52)</b>	(-0.72)	(1.97)	(0.34)	<b>(2.64)</b>	(1.35)
Size					-0.00	-0.05	-0.02	-0.08
					(-0.02)	(-0.42)	(-0.38)	(-0.93)
Bond					-0.03	-0.07	-0.02	-0.04
					(-1.45)	(-1.80)	(-1.08)	(-1.49)
Credit					0.00	0.02	-0.01	-0.01
					(0.10)	(0.38)	(-0.41)	(-0.24)
PTFSBD							0.01	0.02
							(0.97)	(1.65)
PTFSFX							0.03	0.06
							<b>(4.31)</b>	<b>(4.73)</b>
PTFSCOM							0.01	0.02
							(1.21)	(1.83)
PTFSIR							0.01	0.01
							(1.08)	(0.86)
PTFSSTK							-0.03	-0.05
							<b>(-3.17)</b>	<b>(-3.31)</b>
TRENDSTK	0.10	0.14	0.09	0.15	0.09	0.16	0.12	0.20
	<b>(4.30)</b>	<b>(3.38)</b>	<b>(3.31)</b>	<b>(3.36)</b>	<b>(3.38)</b>	<b>(3.52)</b>	<b>(4.75)</b>	<b>(5.13)</b>
$R^2$	0.20	0.14	0.23	0.14	0.26	0.21	0.53	0.56

We saw there are five option factors in Fung-Hsieh model, each written on an index representing an asset class. Since our factor trades 50 futures, one could argue our model has a higher R-squared due to the diversity of underlyings and not due to the actual construction of the factor. To test it, we created a factor trading only a selection of futures. Six were selected, one for each sector: S&P500, US10Y T-note, EUR/USD, Corn, Gold and Crude Oil. Results are presented in Table 1.16. R-squared of all specifications are indeed lower to their counterparts in the benchmark model, reaching 50% in the full specification (4). However, TREND loading remains significant with t-statistic around 6 in specifications (1)-(3). In (4), beta is 0.38 and t-statistic is 3.93. Moreover, it is at the expense of the PTFS factors, since only the FX

Table 1.15 – Regression (full specification) of GM and CTA indexes with Fung and Hsieh nine factors and TRENDXXX, where XXX denotes the asset class specified at the top of the table (COM for commodities, FX for currencies, STK for stocks and BD for bonds and interest rates). T-statistic is displayed below the coefficients.

	<i>(Commodities)</i>		<i>(Currencies)</i>		<i>(Equities)</i>		<i>(Bonds)</i>	
	<i>(COM)</i>		<i>(FX)</i>		<i>(STK)</i>		<i>(BD)</i>	
	GM	CTA	GM	CTA	GM	CTA	GM	CTA
Alpha	-0.18%	-0.24%	-0.17%	-0.24%	-0.01%	0.06%	-0.12%	-0.16%
	(-1.06)	(-0.88)	(-1.02)	(-0.88)	(0.03)	(0.26)	(-0.66)	(-0.58)
Equity	0.19	0.23	0.21	0.26	0.11	0.09	0.20	0.25
	<b>(4.92)</b>	<b>(3.66)</b>	<b>(5.29)</b>	<b>(4.10)</b>	<b>(2.64)</b>	(1.35)	<b>(4.90)</b>	<b>(3.76)</b>
Size	-0.04	-0.11	-0.04	-0.12	-0.02	-0.08	-0.07	-0.16
	(-0.66)	(-1.22)	(-0.75)	(-1.30)	(-0.38)	(-0.93)	(-1.10)	(-1.65)
Bond	-0.04	-0.07	-0.03	-0.07	-0.02	-0.04	0.01	0.02
	(-1.87)	<b>(-2.25)</b>	(-1.67)	<b>(-2.09)</b>	(-1.08)	(0.58)	(-1.97)	(0.43)
Credit	-0.02	-0.03	-0.02	-0.03	-0.01	-0.03	-0.03	-0.05
	(-0.76)	(-0.62)	(-0.78)	(-0.65)	(-0.41)	(-0.97)	(-0.96)	(-0.84)
PTFSBD	0.01	0.03	0.02	0.05	0.01	0.02	0.00	0.01
	(1.04)	(1.70)	<b>(2.17)</b>	<b>(2.88)</b>	(0.97)	(1.65)	(0.14)	(0.58)
PTFSFX	0.02	0.04	0.01	0.02	0.03	0.06	0.03	0.05
	<b>(3.03)</b>	<b>(3.33)</b>	(0.99)	(1.12)	<b>(4.31)</b>	<b>(4.73)</b>	<b>(3.18)</b>	<b>(3.45)</b>
PTFSCOM	-0.01	-0.01	0.00	0.01	0.01	0.02	0.01	0.02
	(-1.00)	(-0.55)	(0.06)	(0.57)	(1.21)	(1.83)	(0.77)	(1.30)
PTFSIR	0.01	0.01	0.00	0.00	0.01	0.01	0.00	0.00
	(0.60)	(0.35)	(0.29)	(0.02)	(1.08)	(0.86)	(0.41)	(0.16)
PTFSSTK	-0.01	-0.02	-0.01	-0.02	-0.03	-0.05	-0.01	-0.01
	(-1.39)	(-1.36)	(-1.71)	(-1.72)	<b>(-3.17)</b>	<b>(-3.31)</b>	(-0.57)	(-0.47)
TRENDXXX	0.07	0.13	0.08	0.14	0.16	0.20	0.08	0.14
	<b>(4.05)</b>	<b>(4.19)</b>	<b>(3.62)</b>	<b>(3.89)</b>	<b>(4.75)</b>	<b>(5.13)</b>	<b>(2.29)</b>	<b>(2.53)</b>
$R^2$	0.50	0.51	0.48	0.50	0.53	0.56	0.42	0.44

one is still significant after adding the reduced trend factor. These results are not surprising: one of the major characteristics and advantages of the trend following strategy is its diversification and the fact it trades several futures from all asset classes. Trading six out of fifty futures does not change the transparency and replicability of our factor, so one cannot argue the factor is a sophisticated strategy.

Table 1.16 – Regressions of GM and CTA HFR indexes with a TREND factor built on a selection of futures (one per asset class): S&P500, US10Y T-note, EUR/USD, Corn, Gold and Crude Oil. T-statistic is displayed below the coefficients.

	(1)		(2)		(3)		(4)	
	GM	CTA	GM	CTA	GM	CTA	GM	CTA
Alpha	-0.01%	-0.17%	-0.24%	-0.30%	-0.26%	-0.37%	-0.26%	-0.39%
	(-0.38)	(-0.80)	(-1.84)	(-1.41)	(-1.96)	(-1.71)	(-1.43)	(-1.34)
Equity			0.14	0.11	0.15	0.14	0.17	0.20
			<b>(4.60)</b>	<b>(2.04)</b>	<b>(4.22)</b>	<b>(2.41)</b>	<b>(4.37)</b>	<b>(3.13)</b>
Size					-0.04	-0.11	-0.05	-0.13
					(-0.67)	(-1.18)	(-0.82)	(-1.38)
Bond					-0.02	-0.04	-0.02	-0.04
					(-0.93)	(-1.31)	(-0.85)	(-1.21)
Credit					-0.04	-0.05	-0.04	-0.06
					(-1.21)	(-1.01)	(-1.32)	(-1.23)
PTFSBD							0.01	0.02
							(0.77)	(1.38)
PTFSFX							0.02	0.03
							<b>(2.07)</b>	<b>(2.28)</b>
PTFSCOM							0.00	0.01
							(0.25)	(0.77)
PTFSIR							-0.00	-0.01
							(-0.17)	(-0.46)
PTFSSTK							-0.01	-0.02
							(-1.53)	(-1.53)
TRENDSEL	0.24	0.49	0.28	0.52	0.28	0.52	0.22	0.38
	<b>(4.47)</b>	<b>(6.05)</b>	<b>(5.80)</b>	<b>(6.45)</b>	<b>(5.70)</b>	<b>(6.26)</b>	<b>(3.66)</b>	<b>(3.93)</b>
$R^2$	0.21	0.33	0.39	0.37	0.41	0.41	0.48	0.50

## 1.6.2 Cross-sectional momentum

As explained in the literature review, momentum was historically a cross-sectional factor, constructed across individual stocks. Time-series momentum, the main methodology behind our TREND factor, is very different since it is directional and does not rely on the comparison of individual futures' past trend. However, the equity market is one of the major financial markets and the momentum forces that drive both types may be common, making the comparison of factors interesting. Also, many hedge fund strategies are focused on equity and it can be interesting to include in the comparison the equity momentum factor. We therefore add the cross-sectional equity

momentum factor (WML) to our specification and check to what extent it improves the understanding of hedge fund styles. More precisely, we test two new specifications. The first one consists in regressing each HFR index on all Fung-Hsieh factors, and the WML factor. Table A10 in Appendix reports the results. We obtain that WML is significant among 4 styles: Systematic Diversified, Event Driven, Equity Hedge and Relative Value.  $R^2$  increases from 38 to 42% on Systematic Diversified, which is low in comparison to the increase from 38 to 82% with TREND. It is a first evidence our TREND factor brings something else than the standard WML. The fact WML is significant for some equity-related styles but not Global Macro confirms this result. In conclusion, WML does not replace TREND.

The second specification we test consists in regressing each HFR index on all Fung-Hsieh factors, the WML and the TREND factors. Table A11 in Appendix reports the results. The significance of WML factor for the Systematic Diversified style vanishes, in favor of the TREND factor. Moreover, Global Macro and Fund of funds have a significant exposure on TREND. Equity Quantitative Directional is no longer exposed to TREND (nor to WML) when both factors are considered.

All these results confirm that WML and TREND factors are two different factors, TREND explaining both directional strategies (Systematic Diversified and Global Macro), and WML being priced among equity-related styles.

## 1.7 Conclusion

We introduce a transparent cross-asset factor, based on the time series momentum methodology [82, 17] that shows good performances during the 2008 crisis, thus making it a potential candidate for explaining the differences in performance within the hedge fund industry during this period.

This chapter investigates the presence of a trends exposure across the

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various hedge fund styles. We first confirm it in the CTA/Managed Futures style, but more surprisingly, we also detect it in other strategies such as Global Macro, Fund of Funds and Equity Quantitative Directional. The significant improvement in the explanatory power of the factor model we propose is the confirmation that TREND is a strong driver of the alternative space returns.

We look at the contribution of our TREND factor relative to the Fung-Hsieh options factors and we confirm the cross-asset and dynamic characteristics are decisive. Thanks to the transparency feature of our construction, we are able to dig into the TREND exposure and understand where it comes from. Indeed, indexes as well as individual funds are not all equal in terms of the type of trends they are exposed to, hereby differentiating trends on the different asset classes, or trends on different lookback windows.

We retrieve returns data as well as fund characteristics from the Euro-Hedge database and analyze in the cross-section the variation of the TREND loading. The quantile portfolios we form indicate a positive risk-adjusted return associated to an increase in the TREND beta. Some funds do not exhibit any TREND exposure, whereas some funds have a beta close to 0.70. All other things equal, a TREND exposure is associated with a lower return and a lower maximum drawdown outside the Managed Futures space. Focusing on Managed Futures funds only, results of both specifications are not significant, with a strong heterogeneity. The cross-section variation of returns could be related to either a diversity of systematic strategies, or a diversity in the expertise of trend following, where "alpha" trend following funds wouldn't be well explained by our TREND factor.

Our set of factors can be thought as a toolbox to test the presence of a dynamic management of the leverage within certain styles, by using the *sector*-TREND factors. A natural example is the L/S equity style, where funds are not all the time market neutral, due to potential beta timing. In

that case, we could study to what extent this is optimal in comparison to the addition of a TRENDSTK overlay to a market-neutral core strategy.



## Chapter 2

# Diversifying Trends

This chapter provides a new method to disentangle the systematic component from the idiosyncratic part of the risk associated with trend following strategies. A simple statistical approach, combined with standard dimension reduction techniques, enables us to extract the common trending part in any asset price. We apply this methodology on a large set of futures, covering all the major asset classes, and extract a common risk factor, called CoTrend. We show that common trends are higher for some cross-asset class pairs than from intra-asset class ones, such as JPY/USD and Gold. This result helps to create sectors in a portfolio diversification context, especially for trend following strategies. In addition, the CoTrend factor helps to understand arbitrage-based hedge fund strategies, which by essence are decorrelated with the standard risk factors.

*Keywords:* Time series momentum; Portfolio construction; Factor analysis.

## 2.1 Introduction

Since 2015, the trend following space of the hedge fund universe suffers from either flat or negative performance.<sup>1</sup> The 2015-2018 period corresponds to the longest historical drawdown of the strategy, known for exhibiting such long but not deep drawdowns. This characteristic explains why CTA funds and trend following ones in particular are described as a divergent, convex or even positively-skewed strategy. Such stylized fact is at the opposite of what is observed on negatively-skewed strategies. Long-only equities, relative value, carry and other convergent strategies, exhibit short but very large drawdowns. Understanding why drawdown shapes are different is then of primary importance for investors. In the literature, much analysis is done about the time-series view of drawdowns, with quantile measures of drawdowns' distribution such as Conditional Expected Drawdown (also called Conditional Drawdown-at-Risk for an evident parallel). However, little is done on the cross-sectional side of drawdowns or, in other terms, the extent to which drawdowns are coming from a lack of portfolio diversification.

In this paper, we introduce a new cotrend measure with the objective to quantify diversification not in general, but specifically for portfolios or strategies playing simultaneously directional bets on many markets. In this case, the primary risk is to play the same trend through apparently diversified positions. We then introduce a dependance measure between trending markets, and use it to disentangle the common and the idiosyncratic parts in market returns. From a diversification perspective, and in particular to control drawdowns at the portfolio level, the most interesting markets are the ones exhibiting idiosyncratic and diversifiable trends rather than common

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1. Indeed, the main benchmark of this style, the Société Générale CTA Index, displays four disappointing yearly performances: 0.03% in 2015, -2.87% in 2016, 2.48% in 2017 and -5.84% in 2018. The Société Générale Trend index, composed only of the largest trend followers within the style, exhibited similar performances.

trends.

We reach this goal through a two-step approach. First, we use a multiple change regression model to identify trends individually on each market. Doing this analysis pair-wise, we then define a distance between two markets in terms of trends. The generalization of this approach to a set of markets results in a cotrend matrix, which has a particular structure when trends observed across markets have the same economic sources. We use this property to extract a cotrend factor, which represents the common trend component in market returns.

We contribute to the existing literature in two ways. First, in terms of portfolio construction, we propose a new measure of portfolio diversification, adapted to trend strategies. Markowitz (1952) [79] and Sharpe (1964) [91] define optimal portfolios with assumptions on financial assets such as return stationnarity, absence of serial correlation and return normality. However, actual asset returns sometimes deviate from these assumptions. Kahneman and Tversky (1979) [64] show there are behavioral biases which result in decisions inconsistent with the utility theory, and they propose an alternative theory called the prospect theory. Based on this work, Barberis et al. (1998) [20] extended it to finance by presenting anomalies related to these behavior biases. Hurst (2013) [58] provide a recap of the biases that make changes between fundamental values not instantaneous, thus creating trends and then non-stationnarities. Another reason why the standard approach has to be reconsidered for trend following strategies is that the first risk perceived by investors is not a volatility risk, but a drawdown risk. Interesting ideas can be taken from the industry, since they deal with these issues from an empirical standpoint. The stylized facts presented earlier are all related to the apparition of drawdowns, each in its own way. Magdon and Ismail (2006) [78] is the main theoretical reference when it comes to analysing drawdown. They show the expected value of a drawdown depends on the value of the drift and

derive its asymptotic properties. Chekhlov, Uryasev and Zabranakin (2003) [29] and Molyboga (2016) [81] take into account the path followed by prices to build optimal portfolios, applying a CVaR-like statistic on the drawdowns distribution. Lohre et al. (2007) [77] also use alternative risk measures in a portfolio construction context and manage to isolate the quality of prediction of the downside risk, thanks to putting the future returns in the optimizer (called ‘perfect foresight of expected returns’). Strub (2012) [96] uses similar tail risk measures in a trading context, for controlling for the risk of the positions in a trend following strategy. Goldberg and Mahmoud (2016) [51] show this conditional expected drawdown (CED) or Conditional Drawdown-At-Risk (CDaR) is related to the serial correlation of the asset. Rudin (2016) [88] use Magdon-Ismail (2006) [78] formula of expected drawdown to form optimal portfolios, while incorporating investor views on expected returns at the same time. However, these statistics are not the empirical counterparts of a particular moment of the return distribution, resulting in the absence of simple estimators. Moreover, numerical resolution is necessary to calculate optimal portfolios. Our approach provides a new way to analyze drawdowns of trend following strategies, and especially understand to what extent they are due to numerous losses across positions or individual large losses. Contrary to what is standard in the literature on the matter, which is to analyze the length or the depth of drawdowns in the time-series dimension, we focus here on the cross-sectional dimension.

Our second contribution to the literature concerns the standard factor model widely used to decompose CTA performances. We know from the first chapter of this thesis that current models such as Fung, Hsieh (2001) [46] or Agarwal, Naik (2004) [5] do not work on this strategy. Bai, Perron (1998) [10] develop a method to estimate a locally linear regression, which consists in the identification of breakpoints by minimizing squared residuals. Smith (2018) [95] applies a Bayesian panel regression on a cross-section of stocks

and shows that a multivariate approach brings improvement in the break detection in univariate time series. Our contribution is to use Bai, Perron (1998) [10] in a multivariate context to define a CoTrend measure between markets and extract a new factor that captures the commonality in trends between markets.

A first result lies in the description of commonality between trends observed on several markets. We test whether the classification obtained in our context is different from the one obtained with the standard correlation measure. We find interesting cross-asset class pairs that do not show up when looking at standard daily correlations, such as JPY/USD and Gold markets. A qualitative interpretation is that long-term movements are related to economic cycles. For example, these two assets can be seen as safe haven assets, and can 'correlate' (in our way) in the sense market participants go and leave this markets at similar dates. Further work on the identification of the relation with macroeconomic indices would be of interest. The inclusion of our factor in the standard factor model gives new perspectives to understand the cross-section of hedge fund returns. We find significant CoTrend exposures on Event-Driven, Equity Hedge and Convertible Arbitrage strategies. We relate the exposure of these arbitrage strategies to a tail risk exposure.

Practical applications are twofold. A fund manager can use our new risk model to build a well-diversified portfolio, not only in terms of daily volatility but also in terms of drawdowns. Another potential application is from an investment standpoint: the non-diversifiable part of the drawdown risk may imply an alternative risk premium, that may be an interesting additional source of returns. Moreover, an institutional allocator may profit from this decomposition through analyzing the potential funds he could invest in by the lens of this new alternative risk premium benchmark. A better differentiation of the hedge fund space is possible.

The chapter proceeds as follows. Section 2.2 describes the methodology

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for identifying breaks and measuring their commonality. Sections 2.3 gives a brief recap of the financial data we use. Section 2.4 contains the empirical applications. Section 2.5 reviews our arguments and concludes.

## 2.2 Measuring CoTrend

Let us consider  $K$  markets simultaneously traded by a trend following fund. We define in this section the CoTrend measure for these  $K$  markets that measures the potential diversification gain within the universe. We then use this measure to build a factor that represents the common trend featured in all markets belonging to the investment universe, i.e. the non diversifiable part in market trends.

The CoTrend measure is obtained following a two-step approach. The first step consists in detecting multiple structural changes on each market following the procedure introduced by Bai, Perron (1998) [10]. In the second step, we introduce a pairwise distance between two markets involving break dates and trend characteristics to construct the CoTrend matrix that positions each market among the others.

### 2.2.1 Multiple Break Detection

In this first subsection, we build on Bai, Perron (1998) to detect multiple structural changes in a trend model, i.e. when asset prices are explained by a linear function of the time index. As we need to filter these trends on  $K$  markets, we decide to present the model as a system of  $K$  regression equations even if the estimation procedure is defined market by market. Basically, we use a simple multidimensional extension of the multiple structural changes in linear regression model of Bai, Perron (1998). All trend parameters, excluding the unknown dates of the breaks, are estimated by minimizing squared residuals.

Let us consider an investment universe involving  $K$  markets, and the following models with  $m_k$  breaks ( $m_{k+1}$  trends) for the price  $y_{k,t}$ , associated with the market  $k$  at time  $t$ , with  $k = 1, \dots, K$ :

$$y_{k,t} = x_t' \delta_{k,j} + u_{k,t}, \quad (2.1)$$

for  $t = T_{k,j-1} + 1, \dots, T_{k,j}$ , for  $j = 1, \dots, m_{k+1}$ ,  $u_{k,t}$  being a zero-mean error term. We use the convention  $T_{k,0} = 0$  and  $T_{k,m_{k+1}} = T$ . The vector of covariates is  $x_t = (1, t)'$ . The vector of regression coefficients  $\delta_{k,j}$  for all  $k = 1..T$  can be represented by the following diagram 2.1.

Table 2.1 – Diagram of the multiple break detection. *Note: Rows refer to the different financial assets, which all have the same historical dates. Each vertical line is a breakpoint that divide the global period into subperiods. Each subperiod has its estimated slope.*

Market 1	$\delta_{1,1}$			$\delta_{1,2}$
Market 2	$\delta_{2,1}$	$\delta_{2,2}$	$\delta_{2,3}$	$\delta_{2,4}$
	...			
Market $k$	$\delta_{k,1}$	...	$\delta_{k,j}$	...
	...			
Market $K$	$\delta_{K,1}$	...		$\delta_{K,m_{K+1}}$

The indices  $(T_{k,1}, \dots, T_{k,m_k})$  correspond to the unknown breakpoints, as illustrated from the previous diagram where they are represented by the vertical lines separating the cells. For example, for the second market, 3 breaks are identified, thus dividing the total period into 4 subperiods. In the example diagram, markets 2 and  $k$  have three synchronous breakpoints, but the latter has an additional one, that is shared with markets 1 and  $K$ . Our goal is then to estimate simultaneously the regression coefficients  $\delta_{k,j}$  together with these break points using  $T$  observations of  $y_{k,t}$ . The multiple changes model 2.1 may be expressed in a matrix form as  $Y_k = \bar{X}_k \delta_k + U_k$  where  $Y_k = (y_{k,1}, \dots, y_{k,T})'$ ,  $U_k = (u_{k,1}, \dots, u_{k,T})'$ ,  $\delta_k = (\delta_1, \dots, \delta_{m_{k+1}})'$  and  $\bar{X}$  is the matrix which diagonal partition  $X$  at the  $m_k$  partition  $(T_1, \dots, T_{m_k})$ ,

i.e.  $\bar{X}_k = \text{diag}(X_1, \dots, X_{m_k+1})$ . Our objective is to estimate the unknown coefficients  $(\delta_{k,1}, \dots, \delta_{k,m_k+1}, T_{k,1}, \dots, T_{k,m_k})$ .<sup>2</sup>

We follow Bai, Perron (1998) and first assume that the breaking points are known and discuss later the method of estimating it. Under this assumption, a simple least-squares approach applied equation by equation can be used. For each  $m_k$  partition  $(T_{k,1}, \dots, T_{k,m_k})$  denoted  $\{T_{k,j}\}$  the least-squares estimate of  $\delta_k$  is obtained by minimizing the following criteria:

$$\sum_{i=1}^{m_k+1} \sum_{t=T_{k,i-1}+1}^{T_{k,i}} [y_{k,t} - x'_t \delta_{k,i}]^2. \quad (2.2)$$

Let  $\hat{\delta}(\{T_{k,j}\})$  denote the resulting estimate for market  $k$ . Bai, Perron (1998) suggest an "in-sample-like" approach that substitutes  $\hat{\delta}(\{T_{k,j}\})$  in the objective function associated with Equation 2.1 and denotes the resulting sum of squared residuals  $S_T(T_{k,1}, \dots, T_{k,m_k})$ . The estimated break points  $(\hat{T}_{k,1}, \dots, \hat{T}_{k,m_k})$  are such that:

$$(\hat{T}_{k,1}, \dots, \hat{T}_{k,m_k}) = \arg \min_{(T_{k,1}, \dots, T_{k,m_k})} S_T(T_{k,1}, \dots, T_{k,m_k}), \quad (2.3)$$

where the minimization is taken over all possible partitions  $(T_{k,1}, \dots, T_{k,m_k})$ . A potential partition is such that  $T_{k,i} - T_{k,i-1} > q, i = 1, \dots, m_k+1$ , with  $q$  a fixed parameter.

Bai, Perron (1998) [10] displays all the statistical properties of the estimators under a classic set of assumptions. However, this approach is fundamentally in-sample and difficult to apply in an out-of-sample context, i.e. when we want to filter online trends with a continuous arrival of new prices. Indeed, if we add observations at the end of the initial sample to update the time series, the new estimators obtained on the extended dataset could lead to different break point estimates. For this reason, we choose to de-

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2. As in Bai, Perron (1998), no continuity restriction is imposed at the turning points.

Figure 2.1 – Example of a break detection.



velop our own backward-looking estimation procedure for the break point estimation, i.e the second step in the Bai, Perron (1998) procedure. For any date  $t$  belonging to  $(0, \dots, T)$ , we estimate the  $j$  first break dates without any information available after  $t$ . This logic implies that each new observation does not modify the estimation of the past break points. We can extend any period and only detect new breaking points, leaving unchanged the estimation of the previous breaking points.

The intuition we follow is coming from the drawdown measure widely used in the hedge fund industry. A loss particularly all the more hurts the investor if it increases a preexisting cumulative loss, as defined by the log-difference between the last high and the current level of the fund net asset value. An investor positioned short the financial asset would have opposite returns, transforming upward periods into losses, and reverse. By symmetry, we can also introduce a "runup" or reverse drawdown, i.e. the gain from the last low observed on the net asset value. Let us first define iteratively the breaching points, dates that will help identify the actual break points. We denote by  $\hat{T}_{k,j}$  the last estimated break point, the following breaching point

$u_{k,j}$  is, for any  $p \in [0; 1]$ :

$$u_{k,j} = \inf[t > \hat{T}_{k,j} : |y_{k,t} - \left( \mathbb{1}_{y_{\hat{T}_{k,j}} > y_{\hat{T}_{k,j-1}}} * \min_{u \in [\hat{T}_{k,j}; t]} y_{k,u} + \mathbb{1}_{y_{\hat{T}_{k,j}} < y_{\hat{T}_{k,j-1}}} * \max_{u \in [\hat{T}_{k,j}; t]} y_{k,u} \right) | > p] \quad (2.4)$$

Now, the next breakpoint estimate  $\hat{T}_{k,j+1}$  is directly:

$$\hat{T}_{k,j+1} = \mathbb{1}_{y_{\hat{T}_{k,j}} > y_{\hat{T}_{k,j-1}}} * \arg \min_{t \in [\hat{T}_{k,j}; u_{k,j}]} y_{k,t} + \mathbb{1}_{y_{\hat{T}_{k,j}} < y_{\hat{T}_{k,j-1}}} * \arg \max_{t \in [\hat{T}_{k,j}; u_{k,j}]} y_{k,t} \quad (2.5)$$

Figure 2.1 displays an illustration of the calculation of  $\hat{T}_{k,j+1}$  from the observation of  $\hat{T}_{k,j}$  and the future price evaluation after this break point. By applying iteratively this approach, we end with the estimated break points  $(\hat{T}_{k,1}, \dots, \hat{T}_{k, \hat{m}_k})$ . The estimates of the regression parameters for the estimated  $m_k$ -partition  $(\hat{T}_{k,j})$  are  $\hat{\delta} = \hat{\delta}(\hat{T}_{k,j})$ . With this estimation strategy, each new point in the sample only modifies the estimation of the regression parameters after the last estimated breaking point.

### 2.2.2 CoTrend Measure

We now have to define a pairwise distance between two markets involving break dates  $(T_{k,j})$  and  $(T_{l,j})$  and trend characteristics  $\delta_k$  and  $\delta_l$ ,  $k, l = 1, \dots, K$ , as defined in the previous subsection. To measure this distance, we first derive the return  $r_{k,t}$  observed on each market from Equation 2.1 as follows:

$$r_{k,t} = \delta_{k,j}^{(2)} + e_{k,t}, \quad (2.6)$$

for  $t = T_{k,j-1} + 1, \dots, T_{k,j}$ , where  $\delta_{k,j}^{(2)}$  is the second component of the vector  $\delta_{k,j}$  and  $e_{k,t}$  is a zero-mean error term.

Let us now define the partition including all the break dates relative to

the two markets,  $(T_{k \cup l, j})$ . We can easily adapt the definition of  $\delta_k$  and  $\delta_l$  to correspond to the new bivariate partition involving  $m_k + m_l$  dates. We use this new partition to decompose the covariance between the returns associated with the two markets and defined in Equation 2.6. We get:

$$\begin{aligned}
 \text{Covariance} &= \sum_t (r_{k,t} - \bar{r}_k)(r_{l,t} - \bar{r}_l) & (2.7) \\
 &= \sum_{i=1}^{m_k+m_l+1} \sum_{t=T_{k \cup l, i-1}+1}^{T_{k \cup l, i}} (r_{k,t} - \bar{r}_k)(r_{l,t} - \bar{r}_l) \\
 &= \sum_{i=1}^{m_k+m_l+1} \sum_{t=T_{k \cup l, i-1}+1}^{T_{k \cup l, i}} \left( r_{k,t} - \delta_{k,i}^{(2)} + \delta_{k,i}^{(2)} - \bar{r}_k \right) \left( r_{l,t} - \delta_{l,i}^{(2)} + \delta_{l,i}^{(2)} - \bar{r}_l \right) \\
 &= \sum_{i=1}^{m_k+m_l+1} \sum_{t=T_{k \cup l, i-1}+1}^{T_{k \cup l, i}} (r_{k,t} - \delta_{k,i}^{(2)})(r_{l,t} - \delta_{l,i}^{(2)}) \\
 &+ \sum_{i=1}^{m_k+m_l+1} \sum_{t=T_{k \cup l, i-1}+1}^{T_{k \cup l, i}} (\delta_{k,i}^{(2)} - \bar{r}_k)(\delta_{l,i}^{(2)} - \bar{r}_l) \\
 &+ \sum_{i=1}^{m_k+m_l+1} \sum_{t=T_{k \cup l, i-1}+1}^{T_{k \cup l, i}} (\delta_{k,i}^{(2)} - \bar{r}_k)(r_{l,t} - \delta_{l,i}^{(2)}) \\
 &+ \sum_{i=1}^{m_k+m_l+1} \sum_{t=T_{k \cup l, i-1}+1}^{T_{k \cup l, i}} (r_{k,t} - \delta_{k,i}^{(2)})(\delta_{l,i}^{(2)} - \bar{r}_l)
 \end{aligned}$$

This calculation just shows that we are able, using partitions, to decompose the covariance into four terms. The first term has a *within trends* financial interpretation. It corresponds to the part of the total covariance that is coming from the statistical dependence around the trends identified for the two markets. The second term has a *between trends* financial interpretation. It corresponds to the part of the total covariance that is coming from the trends observed on the two markets. Last two terms correspond to the interactions between both.

Let us develop the financial interpretation relative to the second term in the decomposition. If we observe only one trend on each market, then this term is equal to zero and the total covariance only comes from the noise observed around this unique trend. If we observe multiple trends on each market, then this second term in the decomposition increases as the deviations to the mean return are observed in the same direction. This term can then measure a dependance between market trends when multiple changes are observed.

Applying this approach to  $K$  markets traded together in the investment universe, we can then define a *between trends* covariance matrix that only focuses on the trend-related dependance. We can then generalize the standard statistical methods to sum up the information contained in a covariance matrix. For example, a basic approach is to compute a PCA of the total covariance matrix. This PCA gives the first common factor describing all the dependences observed between markets. We can follow the same logic and compute the PCA of the *between trends* matrix. The first component or factor captures the CoTrend dimension in the investment universe. If a market has a low beta against this factor, he has a high diversification power. On the contrary, if the beta is high, the diversification power is low.

## 2.3 Data

We introduce in this section the various datasets we use to empirically test the methodology described in the previous section. They essentially relate to futures prices for markets traded by CTA funds.

### 2.3.1 Futures

Our sample consists in 50 futures across the main asset classes: equities, bonds, interest rates, currencies, metals, energies and agriculturals. It has been described in detail in the section 1.3.1 of the previous chapter, and we only focus here on the particular features related to CTA diversification.

Table 2.2 – Summary statistics of our continuous futures. *Note: Ann. return refers to the annualized return in %, annualized volatility, value-at-risk (VaR) and maximum drawdown (MDD) are also expressed in %, S and K stand for skewness and kurtosis, whereas  $\rho$  is the first-order autocorrelation.*

	Ann. Ret.	Vol.	VaR (95%)	MDD	S	K	$\rho$
Emini_DJIndex	6.13	16.35	1.49	-53.65	-0.06	15.06	-0.02
Emini_SP500	4.22	18.26	1.71	-63.47	-0.24	11.59	-0.02
Eurostoxx50	1.40	22.79	2.27	-68.16	-0.15	7.19	0.02
DAX	4.79	21.80	2.13	-75.30	-0.30	8.71	0.03
SMI	3.28	17.82	1.69	-57.06	-0.34	10.57	0.06
Footsie	2.50	17.05	1.68	-57.17	-0.17	7.37	0.02
CAC40	3.08	21.20	2.09	-67.20	-0.09	7.15	0.02
US10YTnote	3.46	5.84	0.59	-14.06	-0.14	6.01	0.02
US2YTnote	1.35	1.58	0.16	-4.46	0.06	7.76	0.02
US5YTnote	2.57	17.80	0.40	-46.07	0.01	23.40	-0.48
Bobl	2.69	3.06	0.31	-8.29	-0.24	5.22	0.01
BundDTB	3.97	5.12	0.52	-11.58	-0.21	4.92	0.02
Schatz	0.82	1.16	0.12	-4.63	-0.31	7.49	0.05
EuroDollar	0.52	0.64	0.06	-2.47	0.49	21.58	0.08
Euribor	0.23	0.37	0.03	-2.28	0.88	20.33	0.16
CHF_USD	0.67	11.36	1.12	-51.01	0.94	27.62	0.01
EUR_USD	-0.06	9.69	0.99	-35.54	0.17	5.39	0.02
GBP_USD	0.84	9.51	0.92	-40.61	-0.30	9.84	0.04
JPY_USD	-0.97	10.71	1.05	-62.81	0.57	9.63	0.00
Corn	-6.92	24.84	2.48	-90.09	0.05	7.85	-0.02
Soybeans	2.56	22.17	2.18	-51.62	-0.20	6.65	-0.02
Wheat	-10.54	27.42	2.73	-97.47	0.16	6.13	-0.04
Cocoa	-3.84	28.34	2.88	-91.04	0.13	6.09	0.01
Sugar11	-1.22	30.38	3.09	-73.76	-0.19	5.56	-0.01
Copper	4.65	24.56	2.44	-67.60	-0.19	6.97	-0.01
Gold	1.37	15.64	1.50	-62.76	-0.28	10.48	0.01
Silver	0.63	27.43	2.68	-73.66	-0.34	9.71	0.01
Platinum	2.35	20.33	1.99	-67.23	-0.47	7.93	0.05
CrudeOil	-0.08	34.25	3.34	-93.34	-0.86	19.56	0.01
NaturalGas	-22.48	46.45	4.68	-99.86	0.07	6.02	-0.01

Table 2.2 contains the univariate statistics for futures returns, with in particular results on drawdowns and runups. Drawdowns are calculated as



the maximum peak to valley performance. The highest observed drawdowns are concentrated in the commodities asset class, with drawdown ranging between -17% and -43%, depending on the considered market. This statistic illustrates the need for diversification when directional positions are opened on these markets. Same conclusions can be made on equity and bond market even if individual drawdowns are of smaller amplitude.

### 2.3.2 Asset pricing benchmark

Our objective in the empirical application part, is to check if a new factor, in the case the cotrend factor, can improve the ability of the factor model to explain the performance of hedge funds. We then start from the nine-factor model of Fung and Hsieh (2001) [46] already described in Section 1.3.1. As before, all the data used in the empirical application are taken from Fung and Hsieh's website.

### 2.3.3 Hedge fund data

Our objective in this paper is to understand the cross-section of hedge fund returns, with a new perspective on the commonality, since measured by our cotrend matrix. To do so, we use the dataset collected from HFR, also already used in section 1.3.1.

Table 2.3 exhibits distribution statistics of the different HFR indexes we use in our empirical application, with a focus on drawdowns. These indexes are heterogeneous in terms of performance and volatility, the latter varying between 3% to almost 12%. Almost all strategies are positively autocorrelated, except the two directional and diversified strategies Systematic Diversified and Global Macro. Moreover, drawdown measures (average and maximum) vary substantially across HFR indexes, with unsurprisingly Short Selling being the one with the largest values. The maximum drawdown varies from

Table 2.3 – Statistics of the returns of HFR indexes, over January 2010 to Mars 2016. *Note: Ann. return refers to the annualized return in %, annualized volatility, average and maximum drawdown (MDD) are also expressed in %, S and K stand for skewness and kurtosis, whereas  $\rho$  is the first-order autocorrelation.*

	Ann. Ret.	Ann. Vol.	$\rho$	S	K	Avg. DD	MDD
Equity Market Neutral	2.86	2.46	0.13	-1.47	8.04	1.51	-6.00
Equity Quant. Directional	4.06	6.68	-0.02	-0.51	3.59	3.84	-13.64
Equity Short Selling	-8.74	9.86	0.05	0.26	2.71	45.39	-67.94
Fund of funds	2.45	3.78	0.15	-0.50	2.59	2.94	-7.24
Systematic Diversified	2.23	7.36	-0.21	0.14	2.13	6.05	-11.96
Convertible Arbitrage	4.27	4.46	0.28	-0.52	3.35	2.64	-9.39
Fixed Income Multistrat.	4.77	3.25	0.32	-0.27	2.74	1.59	-4.68
Event-Driven	4.08	5.44	0.21	-0.58	2.98	3.67	-10.95
Equity Hedge	3.62	7.60	0.05	-0.47	3.35	4.85	-13.79
Global Macro	1.43	4.46	-0.13	0.22	2.35	4.40	-8.17
Relative Value	5.11	3.31	0.30	-0.65	2.96	1.54	-5.78

around -5% for the Fixed Income Multistrategy style to almost -40% for the Short Selling style, but the ranking of styles differs from the one resulting from a volatility risk perspective. This confirms the importance of this type of measure when considering hedge fund strategies.

## 2.4 Empirical Applications

We first apply our multiple break detection method to illustrate on different examples how it works. Not to detect a change in volatility as trends, the returns series is continuously risk-adjusted. Getmansky, Lo and Makarov (2004) [49] identify through a hidden markov model different regimes of volatility. This time-varying feature of the volatility makes the comparison of returns across time difficult. In other words, a daily return of 1% should be considered as a larger movement when it happens in a low volatility period than in a high volatility period. The same applies when considering cumulated returns, or returns over a long period. To have this feature, we need a risk model that takes into account the time-varying feature of the volatility.

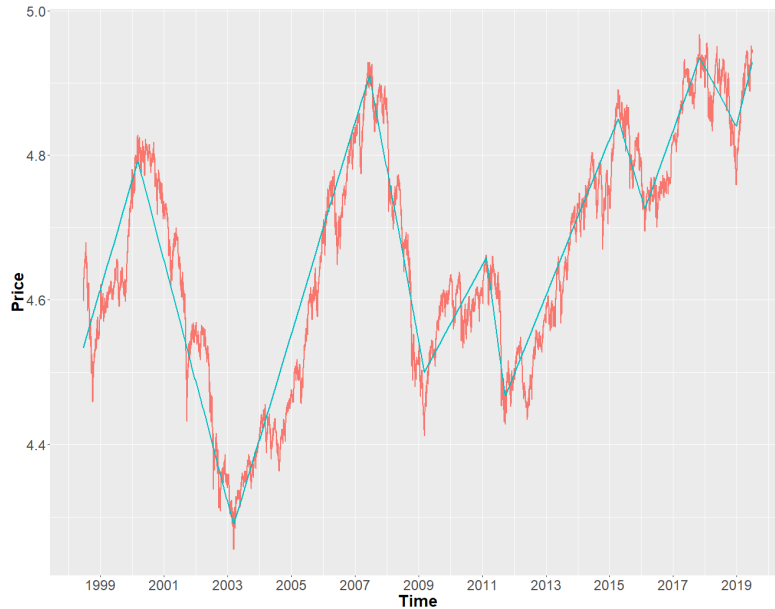
We use the standard practical version of the GARCH(1,1) process, which is the exponentially weighted moving average volatility. The returns adjusted by this volatility now exhibit comparable variations through time. Another benefit of this approach is that it makes financial assets comparable. For example, commodities have a much higher volatility than interest rates. If trends were identified based on cumulated returns on commodity markets, interest rates would never exhibit any trend. Adjusting returns with their volatility allows to identify trends across different types of financial assets.

### 2.4.1 Multiple break detection

We first study to what extent the trends of markets are correlated. Figure 2.2 displays the log-prices of the EuroStoxx50 futures, as well as the estimated breaks and slopes. Despite fixing a minimum threshold to qualify breaks and trends, the identified trends vary substantially in terms of length and slope. The 2001 bubble, the 2008 global financial crisis, the 2011 and 2015 european debt crises are all well identified.

Figure 2.3 extends the previous univariate example to the bivariate case, with the addition of the S&P500 futures. Multiple breaks are also detected on this market and represented along the first time series. The first four breaks of both S&P500 and EuroStoxx50 appear very close, indicating a sensibility to a common trend factor. However, the last two equity drops observed in the european equity market were not present in the main US equity market, indicating a divergence between trends of both markets. Further analysis is needed to test whether this stylized fact is recurrent, by for example analyzing the country-specific european equity markets together and check their commonality with the global european equity market (and the same for US equity markets). Next section aims at describing this commonality in the multivariate case.

Figure 2.2 – Log-prices of the raw market EuroStoxx50 and its associated trends. *Note: The red line correspond to the raw returns of the futures market, and the blue line to the estimated trends.*



We continue to look at potential differences or resemblances across futures and asset classes from a univariate standpoint. Table 2.4 contains statistics related to the multiple break detection method on our set of futures markets. The sample size is equal across all futures markets, so the number of breaks can be interpreted on its own since the number of observations is the same. The average identified length between two successive breaks evolves as much as a factor 2, between 50 days (for Eurodollar) and 78 days (for Bobl). Assuming 22 open days per month, this is between 2 and 4 months. The market with the second shortest trend length is Euribor, which is also a short-term interest rate. The average runup and drawdown variations indicate asymmetries among some futures markets. Bond futures exhibit much larger and longer runups than drawdowns, which is all the more true for the longer maturity markets such as US10Y T-note and Bund. We now infer if there is commonality in the trend statistics within asset classes.

Figure 2.3 – Log-prices of the raw markets S&P500 and EuroStoxx50 and their associated trends. *Note: The red (green) line correspond to the raw returns of the futures market EuroStoxx50 (S&P500), and the blue (purple) line to their estimated trends.*

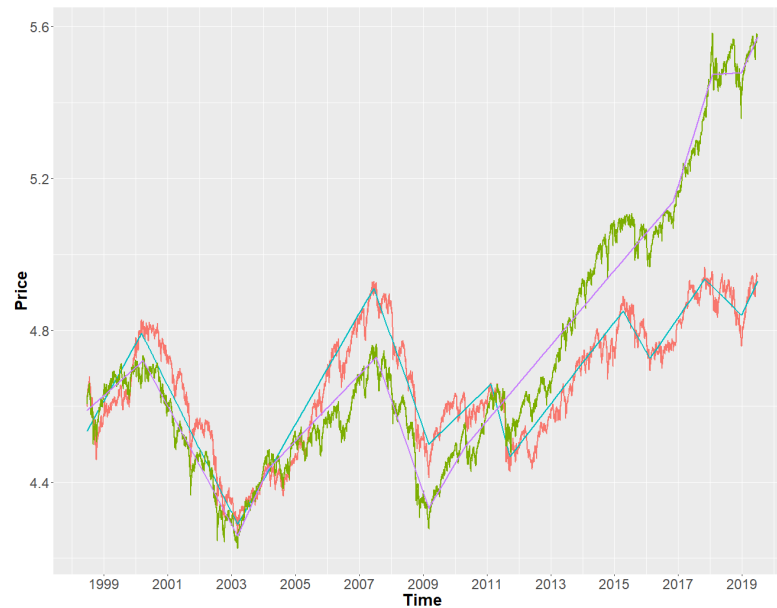
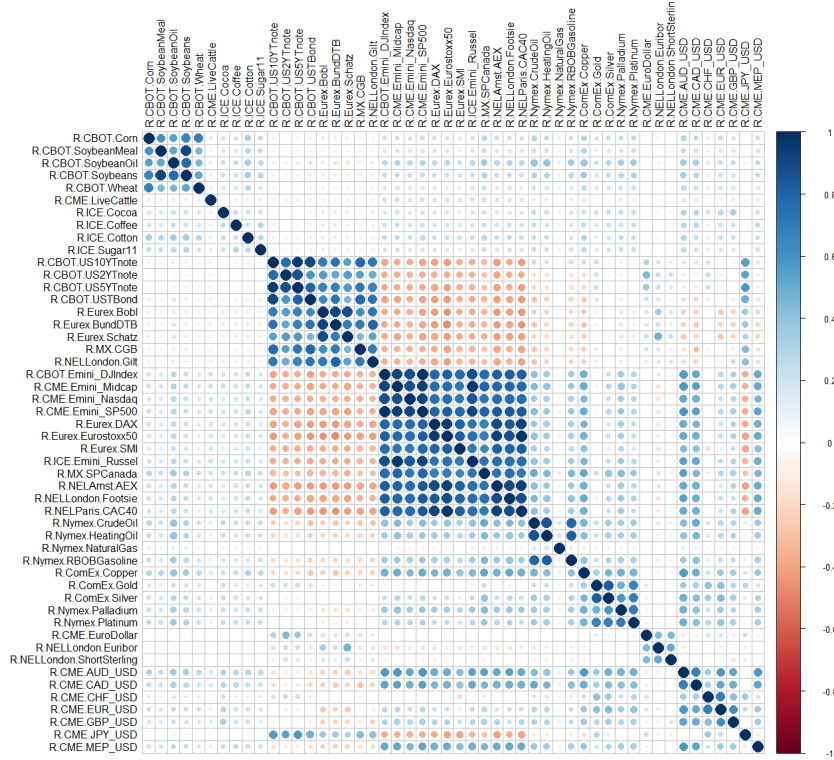


Table 2.5 contains the same statistics than Table 2.4 but calculated at the asset class level, as the simple average of the futures in each asset class. The differences between asset classes first isolate the interest rates sector from the others. Its average trend length is 51 days, whereas other asset classes trend on average during 58 to 65 days. Currencies exhibit the longer trends, around three months on average. Only bonds display an economically significant asymmetry concerning the price variations in upward versus downward trends. However, in terms of duration asymmetry, equity markets and bonds to a lesser extent display longer upward trends than downward ones.

These descriptive statistics help understanding how our multiple break detection method works by giving an overall idea of its results. We identify some differences in the break pattern between individual futures markets and asset classes. However, a close statistic (number of breaks, length and variation of identified trends) is not sufficient to determine if the breaks

Figure 2.4 – Correlation matrix of the 50 futures markets. *Note: Matrix of the standard Pearson correlations calculated on the global sample.*



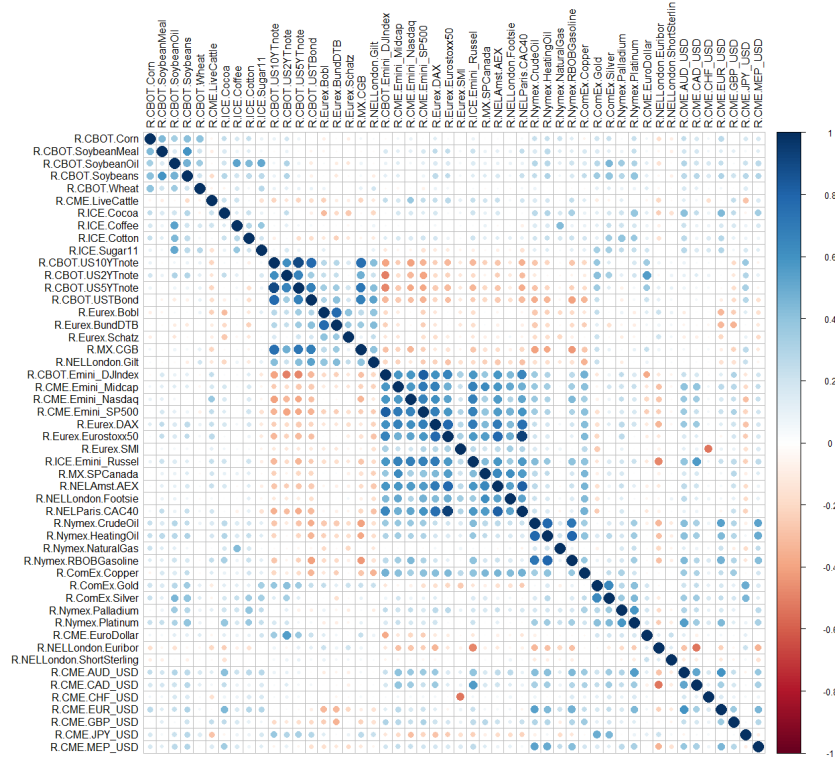
happen around the same time or if the trends are similar.

## 2.4.2 CoTrend matrices

We first study to what extent the market trends are connected. First of all, Figure 2.4 reminds us of the standard Pearson correlation values between the markets. For clarity purpose, markets are ranked in *ex ante* asset classes, Agriculturals, Bonds, Equities, Energies, Metals, Interest Rates and Currencies. The main interpretations are the following: equities and bonds are homogeneous respectively, and anti-correlated, interest rates are homogeneous and different from the rest. The last three asset classes (the three commodity types) are heterogeneous, with various degrees.

Figure 2.5 exhibits the *CoTrend* values. The first thing to say is that

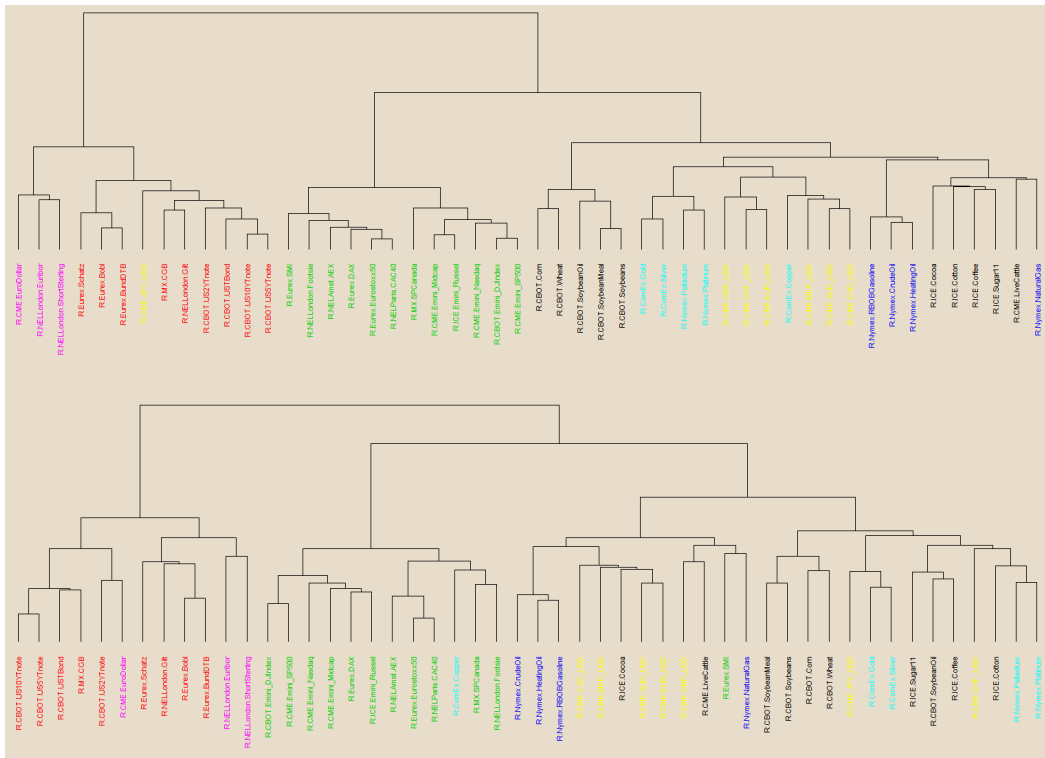
Figure 2.5 – *CoTrend* matrix of the 50 futures markets. *Note: Matrix of CoTrend values calculated on the global sample.*



these values are lower than raw correlations. In the bond space, a separation appears between european and US debt. The Swiss Equity market reveals to be different from the other equity markets. Graphically, we cannot say much about the difference between cross-asset cotrends and correlations. A way to quantitatively interpret all those correlations values is to perform a clustering analysis. Figure 2.6 exhibits the results of the two Hierarchical Cluster Analysis (HCA), one for the raw returns and the second for the signed returns. We used the standard Ward distance (Ward, 1963) [99], that maximises the inter-cluster variance (heterogeneity between groups) and minimizes the intra-cluster variance (homogeneity within groups).

Now, the way to obtain clusters from the tree is to cut it at a certain threshold, for which there is no optimal criterion. The only criteria is the

Figure 2.6 – *HCA* of the 50 futures markets Top figure displays the result for the standard returns, and bottom figure the results for the filtered returns. *Note: Bonds are in red, interest rates in pink, equities in green, currencies in yellow, agriculturals in black, metals in light blue and energies in dark blue.*



elbow method, which basically selects the number of clusters that allow the largest increase in the percentage of variance explained. However, we can constrain this by a minimal and maximal number of clusters, thus reducing the objectivity of the criterion. To understand to what extent *ex ante* asset classes are called into question, we pick as much clusters as the number of them, which is seven.

Table 2.6 displays the obtained clusters, without any row-wise correspondence. The clusters we obtain from the returns are close to the standard asset classes. Indeed, with some differences (such as JPY/USD and Natural Gas), we find the following sectors: Short-Term Interest Rates (STIR), Bonds, Equities, Agriculturals, Energies, Metals, FX. When looking at the



results on the *signed* returns, the first thing to see is the distinction between US and European fixed income markets. Indeed, bonds and interest rates are gathered but splitted across these two geographical universes. Using *ex ante* sectors might not be ideal in terms of diversification when constructing a portfolio, especially in a trend following context where true diversification lies between the trends in markets.

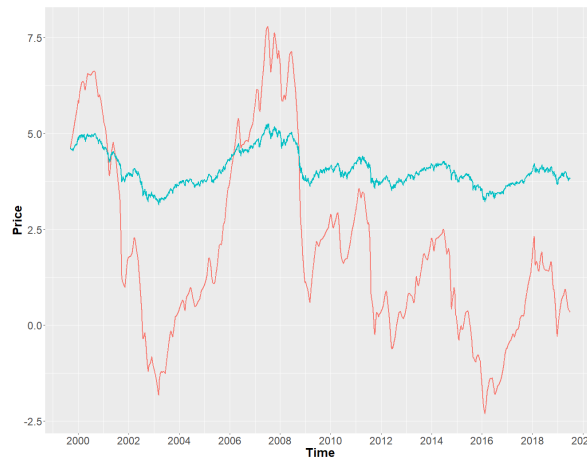
### 2.4.3 CoTrend factor

This paragraph aims at presenting how to extract the CoTrend factor. The standard method to extract statistical factors from data is the Principal Component Analysis (PCA). It was originally applied on data where statistical individuals were actually individuals and therefore inherently independent. Assuming returns have no serial correlation, days can be considered as independent so a PCA is applicable, the variables observed for each day are the different assets. A PCA of single-stocks shows the first factor explains a large portion of the variance (around 90%), partly confirming that a one-factor model is suitable to explain the cross-section of stock returns. The first factor can be interpreted as the portfolio of assets that has the maximum variance, at a fixed total leverage. When projecting variables, or assets in our case, the loss of information is the lowest. The second component is the one minimizing the loss of information when projecting the residuals of the first step.

Naturally, the first principal component embodies the maximum of information regarding the trends identified on each individual futures market. The following components are orthogonal to the first one, where orthogonality is defined as 0 correlation between trends.

Figure 2.7 plots the price series of the CoTrend factor we extracted. We call it the *theoretical* factor since it is a linear combination of filtered returns. However, applying the same weights (the loadings of the first principal com-

Figure 2.7 – Log-prices of the CoTrend factor. *Note: Red line corresponds to the first eigenvector extracted from the  $\delta$  matrix. Blue line corresponds to its counterpart evaluated on raw returns (portfolio of assets whose weights are the loadings of the first eigenvector).*



ponents) on the raw returns yields us the *empirical counterpart* of the factor.

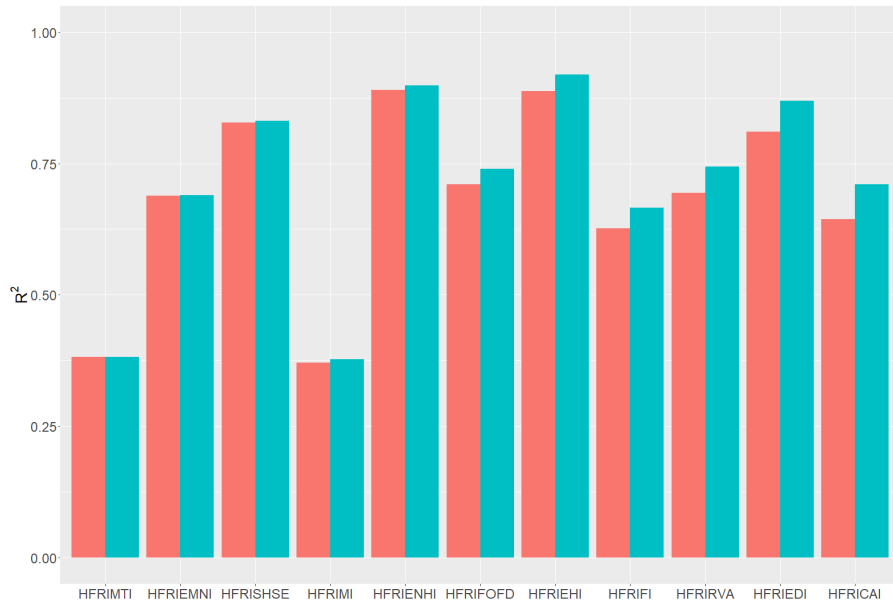
Table 2.7 contains the coefficients of the linear regression of each futures market on the CoTrend factor. All beta coefficients are significant at the 1% level, which is not a surprise since CoTrend is a linear combination of the markets. However, there is variability in the  $R^2$  values, ranging from almost 0 for Gold to 70% for the CAC40 futures. Essentially, the explanatory power is very high for equities and bonds to a lesser extent, and low across the remaining asset classes.

#### 2.4.4 Hedge funds exposure

This section aims at testing whether hedge fund strategies are exposed to the common trends present in the financial markets. A positive and significant beta of an HFR style index would mean this strategy is exposed from a long-only standpoint to the global trends in the financial markets.

CoTrend is significant among seven hedge fund styles, from the highest to the lowest: Event-Driven, Equity Hedge, Convertible Arbitrage, Relative

Figure 2.8 –  $R^2$  of two factor models (9- and 10-factor models) on selected HFR indexes. *Note: Red bars correspond to the Fung-Hsieh 9-factor model, and blue bars correspond to the 10-factor specification, which in addition contains the CoTrend factor.*



Value, Fixed Income Multistrategy, Fund of funds and Equity Quantitative Directional. Systematic Diversified and Global Macro, which we show in Chapter 1 are strongly exposed to the TREND factor, are not significantly exposed to the CoTrend factor. Figure 2.8 displays the improvement in  $R^2$  from the nine-factor Fung-Hsieh model to the ten-factor model, where CoTrend is added. The largest improvement concerns the Convertible Arbitrage style. This is not a surprise since this strategy invests in both individual equities and bonds, which we saw in the previous subsection are largely exposed to the factor.

Despite being extracted from the actual trends across financial markets, CoTrend does not explain the strategies that are exposed to the trend following factor. A "perfect timer" CTA, which switches position on the exact breakpoints, would have a beta to CoTrend that switches from 1 to -1, re-

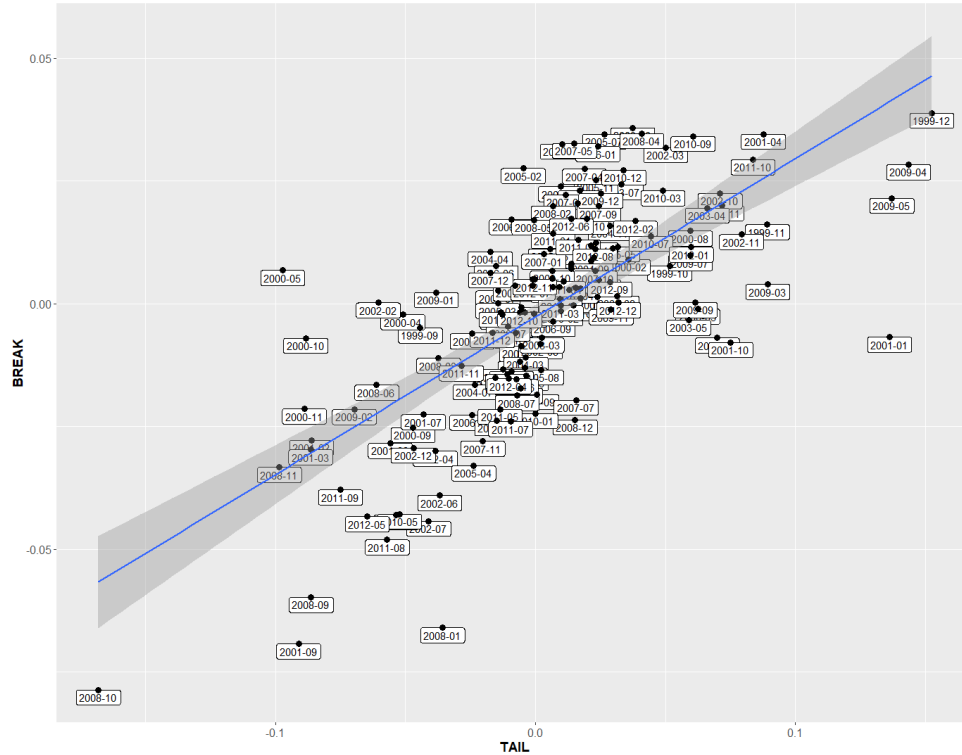
sulting in an unknown overall exposure to the factor. In addition, lag and diversification are mechanisms that should make the strategy returns even more different from an exposure to CoTrend. There are two ways to control for the timing long-short issue. The first one is to evaluate a time-varying beta of the styles on the CoTrend factor, to capture the potential switch from a long exposure to a short exposure. The second way is to create a factor that is myopic to the sign of the trend. We reproduce the same methodology presented in section 2 on the absolute estimated slopes  $|\hat{\delta}(\{\hat{T}_{k,j}\})|$ , the break points estimators staying the same. The resulting factor BREAKABS captures the commonality in the breaks and the trends intensities, without information regarding the directions. Similarly, we estimated the linear regressions of the HFR styles on this factor and Figure A4 and Table A12 in Appendix show the results. As expected, Systematic Diversified and Global Macro are exposed to this factor, though to a lesser extent than the exposure on TREND we identified in Chapter 1. This confirms the importance of the signal lag in the resulting strategy returns.

### **Robustness analysis**

The CoTrend factor is in-sample linear combination of futures returns across a large set of asset classes. The significant exposures of many hedge fund styles could be perceived as the result of overfitting. To control for that, we create a equally-weight long-only factor invested in all futures in the sample, called DIV, and we estimate the linear regressions with this factor instead of CoTrend. For the seven styles significantly exposed to CoTrend, the DIV exposure captures the portion that results from the cross-asset diversified feature. The remaining part, which we expect is positive and represent a large portion of the initial exposure, accounts for the break feature. Figure A5 and Table A13 in Appendix contain the results.

The factor we extract captures the cross-section covariation between the trends and the breaks across many financial assets. Each break can be perceived as tail risk since it is often a return of opposite sign and returns over the preceding trend are stable due to the within trend diversification. Agarwal, Ruenzi and Weigert (2016) [6] analyze whether hedge fund styles are exposed to a tail risk factor. They extract it from individual hedge funds by calculating a tail risk measure and forming long-short quantile portfolios. To test if our CoTrend factor and the TAIL factor are related, we plotted the returns series against each other, as represented in Figure 2.9. The linear relationship appears clearly, with a correlation as high as 70% and a  $R^2$  of the regression of 48%. Further work is needed on that matter to analyze to what extent the exposures on COTREND we identified in the previous section are robust to a TAIL control.

Figure 2.9 – Scatterplot of the CoTrend factor against the TAIL factor (Agarwal, 2016) [6].



## 2.5 Conclusion

We introduce a two-step approach that combines first a statistical method that allows to filter the trends from the time series of financial asset prices, and a standard dimension reduction technique to extract the common trending factor. This new approach therefore models returns as serially dependant, consistently with the momentum anomaly harvested by trend followers. In this context, the commonality of risk between assets can be better understood. This chapter investigates to what extent the relations between assets change when moving from the standard daily correlation space to our *cotrend* space. From this alternative sectorization, we are able to detect relations between markets that weren't captured with standard correlation, but that do make sense from an economic standpoint. Thanks to a standard dimension

reduction technique, we extract the systematic component of risk and show it is priced among certain hedge fund styles. We also provide insights about why CTA and Global Macro strategies are not exposed to it. Further work on this subject would be to relate the returns of the extracted factor to macroeconomic indices, both as a descriptive study and as a predicting exercise thanks to macro news and/or events.

Table 2.4 – Descriptive statistics of the multiple break detection output. *Note: Opposite breaks are only the breaks that signal a change from a upward to downward slope, or the opposite.  $\bar{L}$  is the average length of the trends, in number of open days.  $\bar{\delta}$  is the average daily absolute return of the identified trends, expressed as basis points.  $\bar{L}_{Runup}$  and  $\bar{L}_{Drawdown}$  are respectively the average size (in %) of the upward and downward trends.  $L_{Runup}$  ( $L_{Drawdown}$ ) is the average length of the upward (downward) trends.*

	# of breaks	# of opp. breaks	$\bar{L}$	$\bar{\delta}$	Runup	Drawdown	$\bar{L}_{Runup}$	$\bar{L}_{Drawdown}$
Emini_DJIndex	95.00	75.00	54.55	11.09	8.09	-7.21	64.92	43.02
Emini_SP500	76.00	59.00	68.08	9.74	8.26	-8.17	85.57	46.47
Eurostoxx50	87.00	71.00	60.14	10.27	7.97	-7.52	72.59	47.40
DAX	80.00	65.00	65.40	10.78	8.91	-8.40	79.98	50.08
SMI	90.00	67.00	57.93	11.37	7.48	-8.35	72.02	39.51
Footsie	77.00	64.00	67.38	9.71	7.89	-8.94	84.21	47.17
CAC40	79.00	65.00	66.23	10.02	8.12	-8.56	83.30	45.83
US10YTnote	81.00	64.00	64.52	10.88	10.29	-6.69	84.10	45.41
US2YTnote	88.00	72.00	59.36	10.90	8.53	-7.36	71.37	44.28
US5YTnote	88.00	68.00	59.39	11.06	9.11	-6.78	70.54	47.17
Bobl	67.00	56.00	78.09	11.20	11.20	-8.56	99.11	50.55
BundDTB	80.00	67.00	65.40	12.23	10.82	-7.69	82.81	45.16
Schatz	92.00	77.00	56.87	12.20	9.04	-7.33	65.30	46.83
EuroDollar	104.00	72.00	50.26	11.91	7.44	-6.85	59.68	38.83
Euribor	104.00	73.00	50.31	11.17	6.98	-6.95	52.78	47.07
CHF_USD	82.00	71.00	63.79	9.93	8.19	-7.95	58.34	69.24
EUR_USD	81.00	63.00	64.46	10.70	8.16	-8.73	65.44	63.45
GBP_USD	84.00	72.00	62.29	10.79	8.22	-8.42	57.48	67.10
JPY_USD	88.00	73.00	59.45	10.72	7.67	-8.20	56.29	62.35
Corn	82.00	66.00	63.78	10.67	8.17	-8.40	62.16	65.11
Soybeans	82.00	68.00	63.79	10.83	9.79	-7.27	69.11	59.20
Wheat	78.00	63.00	66.69	10.02	8.43	-8.34	48.65	80.64
Cocoa	89.00	78.00	58.75	11.06	7.53	-8.08	60.21	57.12
Sugar11	83.00	69.00	62.73	11.61	8.77	-8.88	58.10	67.05
Copper	76.00	61.00	68.43	10.14	9.11	-8.09	71.97	65.08
Gold	101.00	81.00	51.50	11.29	8.19	-6.77	54.58	48.24
Silver	91.00	81.00	57.37	11.31	8.90	-7.43	59.72	55.27
Platinum	90.00	72.00	58.04	11.67	8.39	-8.11	64.91	50.53
CrudeOil	85.00	72.00	60.96	11.24	8.35	-9.06	73.63	48.00
NaturalGas	83.00	67.00	63.00	11.38	8.07	-8.87	53.08	70.98



Table 2.5 – Descriptive statistics of the signature outputs per asset class. *Note: Opposite breaks are only the breaks that signal a change from a upward to downward slope, or the opposite.  $\bar{L}$  is the average length of the trends, in number of open days.  $\bar{\delta}$  is the average daily absolute return of the identified trends, expressed as basis points. Runup and Drawdown are respectively the average size (in %) of the upward and downward trends.  $L_{Runup}$  ( $L_{Drawdown}$ ) is the average length of the upward (downward) trends.*

	# of breaks	# of opp. breaks	$\bar{L}$	$\bar{\delta}$	Runup	Drawdown	$L_{Runup}$	$L_{Drawdown}$
Agriculturals	81.40	67.30	64.47	10.69	8.78	-8.16	62.07	66.29
Bonds	84.78	69.44	62.21	11.39	9.61	-7.29	74.97	47.59
Equities	82.36	66.27	63.68	10.54	8.44	-8.08	80.83	44.45
Energies	82.25	67.50	63.33	11.13	8.46	-8.97	70.85	54.69
Metals	90.40	73.60	58.20	11.31	8.74	-7.56	63.82	52.61
Rates	102.67	71.33	50.96	11.45	7.20	-6.75	57.69	42.69
Currencies	81.14	67.43	64.45	10.35	8.25	-8.43	66.48	62.23

Table 2.6 – Clustering ( $n = 7$ ) of raw and signed returns. *Note: there is no correspondance between clusters per row. STIR stands for Short-Term Interest Rates.*

Cluster	Raw returns	Signed returns
1	STIR	US (Bonds + STIR)
2	(US+EU) Bonds + JPY/USD	EU (Bonds + STIR)
3	(US+EU) Equities	Equities (- SMI) + Copper
4	3*Soybean + Corn + Wheat	2*Soybean + Corn + Wheat
5	FX (- JPY/USD) + Metals	JPY/USD + Precious Metals (Gold/Silver)
6	Energies (- NaturalGas)	Non-precious Metals + CHF/USD + SoybeanOil + Coffee + Cotton
7	Other Ags + NaturalGas	Energy + FX (- CHF/USD - JPY/USD) + Cocoa + SMI

Table 2.7 – Regressions of the futures returns on the CoTrend factor.

	Intercept	$\beta$	$R^2$
Emini_DJIndex	0.02	1.91	0.63
Emini_SP500	0.02	2.08	0.66
Eurostoxx50	0.01	2.63	0.70
DAX	0.02	2.58	0.66
SMI	0.02	1.88	0.57
Footsie	0.01	1.98	0.64
CAC40	0.02	2.55	0.70
US10YTnote	0.01	-0.51	0.39
US2YTnote	0.00	-0.12	0.32
US5YTnote	0.01	-0.34	0.38
Bobl	0.01	-0.26	0.37
BundDTB	0.02	-0.44	0.38
Schatz	0.00	-0.09	0.32
EuroDollar	0.00	-0.02	0.07
Euribor	0.00	-0.02	0.10
CHF_USD	0.00	-0.18	0.01
EUR_USD	-0.00	0.09	0.00
GBP_USD	-0.00	0.23	0.03
JPY_USD	-0.01	-0.53	0.15
Corn	-0.03	0.81	0.04
Soybeans	0.02	0.81	0.06
Wheat	-0.05	0.74	0.03
Cocoa	0.01	0.60	0.02
Sugar11	-0.01	0.76	0.03
Copper	0.02	1.65	0.21
Gold	0.03	0.07	0.00
Silver	0.02	0.88	0.05
Platinum	0.02	0.77	0.06
CrudeOil	0.00	1.77	0.13
NaturalGas	-0.10	0.61	0.01

Table 2.8 – Regressions of the HFR indexes on the Fung-Hsieh factors, combined with CoTrend. T-statistic is displayed below the coefficients. *Note: Significant CoTrend exposures are in bold. BD, FX, COM, IR, and STK design respectively the Fung-Hsieh option factors PTFSD, PTFSE, PTFSCOM, PTFSEIR and PTFSESTK.*

	Alpha	BD	FX	COM	IR	STK	Equity	Size	Bond	Credit	CoTrend	R <sup>2</sup>
Eq. Market Neutral	11.62 (1.53)	-0.01 (-1.25)	0.01 (1.61)	-0.01 (-2.60)	-0.00 (-0.39)	-0.00 (-0.22)	0.11 (3.80)	-0.00 (-0.01)	0.01 (1.60)	-0.00 (-0.02)	0.02 (0.33)	0.69
<b>Eq. Quant. Dir.</b>	-2.48 (-0.21)	-0.01 (-1.69)	0.02 (3.17)	-0.01 (-1.28)	0.00 (0.43)	-0.02 (-3.13)	0.34 (7.52)	0.07 (1.83)	-0.00 (-0.05)	0.02 (0.85)	<b>0.22</b> <b>(2.31)</b>	0.90
Eq. Short Selling	-36.92 (-1.65)	0.02 (1.73)	-0.00 (-0.48)	-0.01 (-0.50)	-0.01 (-0.49)	0.00 (0.01)	-0.44 (-5.13)	-0.28 (-3.87)	-0.00 (-0.03)	0.05 (1.39)	-0.21 (-1.14)	0.83
<b>Fund of funds</b>	12.43 (1.16)	0.00 (0.77)	0.01 (2.76)	-0.00 (-0.49)	-0.00 (-0.66)	-0.00 (-0.55)	0.12 (2.86)	0.03 (0.81)	-0.00 (-0.20)	-0.05 (-2.78)	<b>0.23</b> <b>(2.67)</b>	0.74
Systematic Div.	10.00 (0.31)	0.03 (1.91)	0.05 (3.80)	0.01 (0.85)	0.01 (0.32)	-0.02 (-1.14)	0.23 (1.88)	-0.16 (-1.53)	-0.04 (-1.10)	-0.05 (-0.87)	0.03 (0.10)	0.38
<b>Convertible Arb.</b>	25.78 (1.94)	0.00 (0.66)	0.00 (0.80)	-0.01 (-1.66)	-0.01 (-1.22)	-0.01 (-0.98)	0.06 (1.10)	0.05 (1.22)	-0.03 (-1.78)	-0.05 (-2.30)	<b>0.41</b> <b>(3.83)</b>	0.71
<b>Fixed Inc. Mult.</b>	37.52 (3.60)	-0.01 (-0.98)	0.01 (1.83)	-0.00 (-0.91)	0.00 (0.08)	-0.01 (-1.05)	0.04 (1.09)	0.04 (1.09)	-0.03 (-2.60)	-0.08 (-4.20)	<b>0.23</b> <b>(2.74)</b>	0.67
<b>Event-Driven</b>	24.00 (2.20)	0.00 (0.27)	0.01 (1.09)	-0.01 (-2.33)	-0.01 (-1.67)	-0.00 (-0.50)	0.08 (2.04)	0.10 (2.89)	-0.02 (-1.74)	-0.08 (-4.23)	<b>0.47</b> <b>(5.37)</b>	0.87
<b>Equity Hedge</b>	5.18 (0.43)	-0.00 (-0.37)	0.01 (1.97)	-0.01 (-2.69)	-0.01 (-0.88)	-0.01 (-0.93)	0.26 (5.64)	0.17 (4.45)	-0.02 (-1.34)	-0.03 (-1.64)	<b>0.49</b> <b>(5.04)</b>	0.92
Global Macro	8.52 (0.44)	0.02 (1.50)	0.03 (3.63)	0.00 (0.36)	0.00 (0.46)	-0.01 (-1.23)	0.14 (1.94)	-0.06 (-0.95)	-0.02 (-1.06)	-0.03 (-0.97)	0.13 (0.85)	0.38
<b>Relative Value</b>	35.04 (3.78)	-0.00 (-0.63)	0.00 (0.56)	-0.01 (-1.34)	-0.00 (-0.39)	-0.01 (-2.40)	0.03 (0.94)	0.03 (1.17)	-0.03 (-2.92)	-0.07 (-4.08)	<b>0.27</b> <b>(3.55)</b>	0.74

## Chapter 3

# Futures Market Liquidity and the Trading Cost of Trend Following Strategies

We use a unique dataset reporting the trading of an institutional asset manager implementing trend following strategies to estimate the associated transaction costs. With information both at the trade and the fund levels, we disentangle the impact of the execution quality from the management decisions on these costs. We show that the disappointing performances observed for trend following these recent years are explained by a drop in the volatility of the futures markets these strategies generally trade.

*Keywords:* Trading Costs, Market Impact, Liquidity, Trend Following.

### 3.1 Introduction

Trend Following strategies are widely used by investors as a source of performance and diversification for their portfolios. These strategies are now well studied by the financial academic literature, and a range of theoretical explanations are provided to better understand the underlying economic mechanisms. However, their success raises important questions regarding the scalability of such strategies. As they involve particularly high turnover and generate significant transaction costs, their attractiveness for investors may strongly depend on the market impact resulting from their trading.

In this chapter, we use a unique dataset reporting the trading of an institutional asset manager implementing such diversified trend following strategies on a wide set of futures markets. We use information both at the trade level and at the fund level to cover all the investment decisions that ensure clients an optimal exposure to these strategies. We argue in particular that the information at the trade level alone is not sufficient to reach this objective. Indeed, decisions at the fund level may have a huge impact on the amount of capital traded every day, and by direct consequence on the transaction costs paid by investors. Our approach first consists in computing an implementation shortfall indicator for all trades that are generated by the strategy. This indicator basically measures the difference between the market price used to generate a buy/sell signal, and the average price obtained from all trades related to this signal. The bigger the implementation shortfall is, the higher the transaction cost at the individual trade level. However, this indicator only gives a partial view on the final transaction costs borne by investors. Indeed, all these costs must be aggregated at the fund level. This aggregation process is directly impacted by allocation decisions, for example the decision to increase or not the fund leverage.

Although our approach is limited to a single asset manager and a single

investment strategy, it takes into account both the trade-wise and portfolio-wise levels of transaction costs. The alternative approach consists in using bigger databases, such as the one provided by ANcerno. However, this requires a matching procedure to link the trades generated by a strategy to actual trades from the database, to estimate the transaction costs. In our case, we do not have to define such matching procedure, since we possess all the information regarding the reasons why trades are generated.

Our first result is related to the net-of-fee performance of trend following strategies. Using all the information concerning trade execution, we decompose the impact of transaction costs on the performance, at the individual trade level but also at the fund level. We can then evaluate the specific trading costs of each futures market used by the fund. We observe a huge heterogeneity between markets. Moreover, the ranking differs from the one generally obtained when using other transaction cost measures such as the bid-ask spread. Our second result is related to the evolution over time of the total transaction costs paid by investors for trend following strategies. We find that a decrease in the volatility level has a negative impact on these transaction costs. This counterintuitive result can be explained by the adjustment made at the fund level when volatility drops. To maintain the volatility target defined at the fund level, the portfolio manager naturally increases the fund leverage, and by consequence the turnover. If the volatility decrease reduces on average the market impact at the trade level, it increases the total amount of costs paid by investors at the fund level. This result can only be obtained using our dataset, as we get in addition to the information concerning trade-by-trade transaction costs, all the management decisions taken at the fund level to satisfy the fund investment guidelines. Finally, our third result relates to the influence of market conditions on transaction costs. Beyond the volatility drop, the observed drop in the average correlation between markets during the period of 2016-2018 explains the increase

in the total transaction costs. Lastly, we show that specific features of trend following strategies may also have an influence on the total transaction costs.

As chapters 1 and 2, this chapter relates to the literature on time-series momentum performance. Jegadeesh and Titman (1993) [61] is the first paper focusing on the momentum anomaly. It shows that past winners tend to outperform past losers in terms of risk-adjusted returns. In other words, a portfolio long the top decile of the past winners and short the bottom decile harvests alpha on the long run, as measured by the standard Fama-French (1992) [43] factor model. Carhart (1997) [28] extends this work in terms of asset pricing by adding this new momentum risk factor to the Fama, French (1992) [43] model. The economic rationale behind the existence of this anomaly lies in behavioural theory. Indeed, according to its founders Kahneman and Tversky (1979) [64], market participants are not perfectly rational and often take decisions outside the scope of the expected utility maximization framework. These decisions are the result of behavioural biases, and some examples are under-reaction, herding, anchoring, disposition effect. . . Hurst, Ooi and Pedersen (2013) [57] provides a complete review of these biases and explain how these are creating trends in equity markets. However, this anomaly is present not only in the equity markets but across all asset classes as well (Moskowitz, Ooi and Pedersen, 2012 [82], Baltas and Kosowski, 2012 [14]). The financial industry is well aware of the existence of such anomaly, and trend followers, a special kind of CTAs/Managed Futures from the hedge fund space, have been earning strong returns for decades. The past four years have proven difficult for this style and clients as well as managers are wondering about the future of this strategy and want to understand the reasons behind this recent underperformance.<sup>1</sup> Our study contributes to this literature by showing that trading costs may explain part of the disap-

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1. The average annual return of the Société Générale Trend Index is close to -4% the last three years, compared to a previous long-term average close to 10-14%.

pointing performance observed for these strategies. The drop observed in the market volatility has increased the fund turnover and significantly reduced the performance given to investors.

Moreover, this chapter relates to the literature on Transaction Cost Analysis (TCA). The first level of decomposition of transaction costs consists in differentiating explicit from implicit costs. Explicit costs are the ones charged by the broker, the clearer and the exchange to trade, and is a fixed amount per unit of traded quantity. Not much analysis can be done on this matter. Implicit costs are more complex to measure and may depend on many parameters. Indeed, they correspond to the costs of not exactly owning the strategy portfolio, either due to missed trades or to trades realized at a different price than the model price. A first solution to estimate transaction costs is to use the procedure developed in Harris (1989) [54], which consists in estimating the effective bid-ask spread from end-of-day data. Novy-Marx and Velikov (2016) [83] and Chen and Velikov (2019) [30] use this approach to estimate trading costs of a large panel of anomalies including the Carhart momentum. However, this estimate can be quite different from effective transaction costs as it does not account for market impact, i.e. the up/down pressure on prices when we buy/sell. Perold (1988) [87] introduces in his seminal paper the implementation shortfall approach, which decomposes the slippage into different sources of cost, such as delay, bid-ask spread, arrival cost, opportunity cost, market impact... Collins (1991) [32], Wagner (1993) [98], Kissell (2006) [66] and Khandoker (2016) [65] all provide extensions to this decomposition, but the overall idea remains the same. We use the same approach to estimate transaction costs at the individual trade level. These asset-level views of liquidity are interesting when studying how financial markets work. However, from an investment management perspective, the total cost of liquidity should be measured at the portfolio level. Indeed, managing a portfolio comes logically with trading costs, which reduce the



achievable expected return. Both stakeholders, manager and clients, have an interest in monitoring them and assessing the trade-off between the expected return and the trading cost. Frazzini, Israel and Moskowitz (2015) [44] use the proprietary database of AQR asset management trades and find lower transaction costs for institutional investors. Two reasons may explain this result. First, the price impact models employed are generally too conservative and overestimate transaction costs. Second, tick-by-tick database provides average trades, including informed traders, retail traders, liquidity demanders, and those facing high price impact costs. By only considering trades executed by institutional investors, they estimate the real costs paid by their clients. Briere et al. (2019) [26] results on ANcerno database confirm Frazzini, Israel and Moskowitz (2015) [44] findings. Our paper contributes to this literature by including in the estimation of transaction costs all the consequences of the fund management decisions at the trade level, with the market impact generated by the rebalancing procedure, but also at the allocation level, when the management constraints evolve with the financial environment. We obtain the counterintuitive result that a drop in volatility can increase the total amount of transaction costs paid to get an exposure to trend following strategies.

The chapter proceeds as follows. Section 3.2 details the characteristics of the fund management process and the methodology used to quantify transaction costs. Section 3.3 presents the database and the first descriptive statistics illustrating this dataset. Section 3.4 reports the empirical application. Section 3.5 concludes.

## 3.2 Trade execution quality and fund allocation decisions

The implementation cost of a portfolio or a strategy is simply defined as the cost paid by the manager for the whole associated trading activity. To comply with the fund investment objectives, the fund manager makes transactions with the capital he is entrusted with by clients, plus or minus some additional capital used to leverage/deleverage the portfolio to meet investment objectives. Transaction costs can hence be computed both at the trade (i.e. before leverage) level or at the fund (i.e. after leverage) level. The first level reflects the execution quality per trade, defined by the slippage between the executed price and the target price. The second level reflects the result of the aggregation of these costs, weighed by the transaction size, and may be influenced by general market conditions. We detail in this section the approaches used to quantify both of them.

### 3.2.1 Trade execution

Implementation cost is first coming from the execution of individual orders. The corresponding trades are generally executed by algorithms, with the objective to reduce or even reach negative transaction costs. Indeed, the objective of the execution algorithm is to trade all required quantities for the best possible price, that is the closest to the model price or inferior (respectively superior) for a buy (resp. sell) transaction. To do so, the algorithms places limit orders on the supply (resp. demand) side of the order book, hoping for a move in the mid-price to get executed. Should this happen, the obtained price would be better than the model price and the transaction cost negative. However, this trading strategy is not without risk. A move in the opposite direction would leave the limit orders far from the market and new limit orders or market orders should be set. In that case, the executed price

would be worse than the model price.

To better understand this idea, let us detail the practical execution of an order. After receiving the trading instructions, the execution algorithm is launched, and this time is stamped as the time of arrival. The mid-price on the market at this time is called the arrival price. During the trading session, the algorithm slices the original order into smaller orders, also called child orders, that may be market or limit orders. Slicing improves the access to liquidity. Indeed, the market impact of child orders is supposedly reduced due to their smaller quantity. Parent orders are not only sliced into child orders, but these child orders are often spread throughout the trading session. This feature, called order scheduling, helps taking a hidden liquidity. However, there is the risk that child orders are not filled at the end of the day. The fill rate, percentage of filled orders over a day, can be used as a measure of execution quality. Anand et al. (2019) [7] analyze broker's routing behavior and performance through this lens. These non-filled orders can be detrimental to the performance, creating an opportunity cost modeled as the difference between the day closing price and a benchmark price. In our case, non-filled orders are in fact cancelled orders, which were initially limit orders but got cancelled by the algorithm due to adverse market moves, making the initial limit price irrelevant. However, since they represent only about 0.1% of the total orders, we decided to remove them from the analysis. The information contained in our execution set is at the child order level. We focus on the difference between the executed price and the model price, and the latter is necessarily constant across all the child orders related to a parent order. The consequences of slicing and scheduling should be considered in the cost calculation. Our unit and reference for the model is the parent order, where the average executed price is compared to the model price, defined at the beginning of the trading session. The parent order contains the aggregated quantity across all the child orders, and the corresponding average executed

price.

### 3.2.2 Trade execution quality measure

We estimate trend following trading costs by first computing the cost of rebalancing each futures position and then by aggregating them with their respective weights in the portfolio. The total trading cost on each futures is measured as the sum of the implementation shortfall and fixed costs, including commissions taken from the broker, clearer and the exchange. Implementation shortfall, as defined in Perold (1988) [87], measures the difference between a benchmark price and the average traded price, in percent of the benchmark price. The benchmark price can be the price at the time the strategy desired holdings are generated, or the price observed when the trading session starts. In the first case, the calculation includes the delay cost while in the second case, it measures the sole market impact.

For a parent order  $m$  of size  $Q_m$  and side  $S_m$  (1 for a buy order and -1 for a sell order) composed of  $N_m$  child orders, with a respective quantity  $q_i, i \in \{1, \dots, N_m\}$  and executed at a price  $p_i$ , the implementation shortfall is given by Equation 3.1:

$$\text{IS}_m = \frac{S_m}{P_m^{\text{ref}}} \left( \frac{\sum_{i=1}^{N_m} p_i q_i}{Q_m} - P_m^{\text{ref}} \right), \quad (3.1)$$

where  $P_m^{\text{ref}}$  is the price used as reference to compute the implementation shortfall. A major difference we have with the standard implementation shortfall from Perold (1988) is the absence of opportunity cost, which is the cost of not trading. We are in a 'complete execution' situation. All orders are always executed before the settlement of the market. Hence, we have the exact decomposition of quantities:  $Q_m = \sum_{i=1}^{N_m} q_i$ . In that case, the implementation shortfall does not depend on the settlement price of the day. The chosen convention is the standard one, that is to express the Implementation

Shortfall as a cost. A buy order ( $S_m = 1$ ) is costly when the average executed price is above the reference price, which is consistent with our formulation. The implementation shortfall can simplify into:

$$IS_m = \frac{S_m}{P_m^{\text{ref}}} (P_m^{\text{exec}} - P_m^{\text{ref}}), \quad (3.2)$$

where  $P_m^{\text{exec}}$  is the average execution price of the parent order  $m$ . Recent papers studying portfolio transaction costs such as Frazzini et al. (2018) [45] and Briere et al. (2019) [26] also use this implementation shortfall approach. The reference price is a key element of the transaction cost analysis, since the interpretation of this cost will be different depending on the chosen reference price. In our case, we consider the model price as the reference so that the implementation shortfall will stand as the difference between paper trading and live strategies.<sup>2</sup>

A parent order is defined as a pair of a contract and a trading day. This parent order thus contains all the child orders across all portfolios that were executed during this day and on a given contract. These child orders are the result of the execution trader slicing and scheduling the parent order to avoid sending one large order which might move the market and make his order badly filled. However, despite this precaution, there still might be information flow during the trading day creating market impact.

Here, since we have all the information about the composition of the parent order (child level information), we can focus on the evolution of the implementation shortfall within the parent order, on an intraday basis. The mathematics stay almost the same, except for the fact that the average execution price of the parent order is updated during the trading session as child orders get executed. The reference price also stays the same, since it is de-

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2. The reference price may be fixed at the previous day closing price. In that case, movements of price happening between the reference time and the start of the trading session would impact the cost. This approach does not produce a cost that makes sense in the execution setup of the analyzed asset management firm.

terminated before the trading session starts. We accordingly extend Equation 3.1 to get the intraday implementation shortfall for the  $k$ -th child order:

$$\text{IS}_{m,k} = \frac{S_m}{P_m^{\text{ref}}} \left( \frac{\sum_{i=1}^k p_i q_i}{\sum_{i=1}^k q_i} - P_m^{\text{ref}} \right), \quad (3.3)$$

with  $k \in \{1, \dots, N_m\}$ . The last intraday implementation shortfall necessarily equals the parent order level implementation shortfall, i.e.  $\text{IS}_{m,N_m} = \text{IS}_m$ . The intraday implementation shortfall as we define it is a partial implementation shortfall since it is the experienced cost of trading the first  $k$  child orders. If we consider an advantageous price move between the start of the day and the first child order, the first partial implementation shortfall will be negative and the following partial ones will evolve as new trades are executed but still depend on the preceding child orders execution.

### 3.2.3 Fund allocation decisions

Diversification effects between traded markets and strategies within a fund may reduce the fund volatility. To comply with the fund mandate which often involves a target volatility, the portfolio manager thus needs to leverage up the individual positions. The quantities to trade increase and so does the portfolio implementation cost, assuming a fixed trade execution quality. The Implementation Shortfall measures the relative difference between the executed price and the reference price, and the cost in dollar terms is only the difference between these two prices. On a given day, the portfolio cost is thus the sum of all the dollar costs across all corresponding parent orders, taking into account the quantity traded. We define this cost as:

$$\begin{aligned} \text{Portfolio Trading Cost}_t^{USD} &= \sum_{m \in t} Q_m \times S_m \times (P_m^{\text{exec}} - P_m^{\text{ref}}) \\ &= \sum_{m \in t} Q_m \times IS_m \times P_m^{\text{ref}} \end{aligned} \quad (3.4)$$

where  $IS_m$  is the implementation shortfall defined in Equation 3.1. This is thus the dollar amount lost due to trade on a different price than the model price. It is natural to express it as a performance, by dividing it by the total value of the portfolio. In our firm-wide setup, this corresponds to the Assets Under Management (AUM). The portfolio trading cost on a given day, expressed as a performance, is the following:

$$\text{Portfolio Trading Cost}_t = \frac{\text{Portfolio Trading Cost}_t^{USD}}{\text{AUM}_{t-1}}. \quad (3.5)$$

Other costs that come from managing a portfolio and placing trades are explicit costs. In the futures markets, these are taken by three different counterparts: the broker for executing each trade, the clearer for ensuring the settlement and the exchange which charges every transaction made. All three are expressed as a fixed cost: a dollar amount is paid for every lot traded. For the purpose of this study, we aggregate these three sources into what we call fixed costs. The portfolio fixed cost  $\text{Portfolio Fixed Cost}_t^{USD}$ , expressed in dollar terms, is:

$$\sum_{m \in t} Q_m \times (\text{BrokerageFee}_t + \text{ClearingFee}_t + \text{ExchangeFee}_t), \quad (3.6)$$

and, expressed as a performance, corresponds to:

$$\text{Portfolio Fixed Cost}_t = \frac{\text{Portfolio Fixed Cost}_t^{USD}}{\text{AUM}_{t-1}}. \quad (3.7)$$

The portfolio total cost is defined as the sum of these two costs, i.e. the portfolio trading cost and the portfolio fixed cost.

### 3.3 Data

We obtain institutional trading data for the period from January 2010 to December 2018 from a CTA management firm. The core trend following strategies used by this fund manager are based on time-series momentum, which is a simple long/short cross-asset portfolio harvesting trends present in futures markets (see Moskowitz Ooi and Pedersen, 2012 [82] for a general discussion on the robustness of the time-series predictability in futures markets). The investment portfolio is basically long the futures which exhibit a past positive performance and short the ones with a negative past return. The position on any contract only depends on its past prices, and contrary to the original momentum, no cross-section comparison is done. Futures are then given an equal budget of risk and the global portfolio targets a fixed volatility. All portfolios supervised by the fund manager follow the same strategy, although with different investment sets or volatility levels. However, the output of the trading system stays the same, a list of trades on futures contracts. Portfolios are rebalanced at a given frequency. Each time, the system sends a list of trades to perform by the execution algorithm, containing desired quantities and model prices. The trading algorithm does not make any explicit portfolio decision, its objective is only to lower the transaction costs related to slippage.

Our data thus reflects the potential costs faced by investors. The context and the scope of our data are very similar to the paper from Frazzini, Israel and Moskowitz (2018) [45]. However, we analyze global futures instead of single stocks markets. Raw data contains all the trades executed by the fund management firm. All portfolios, funds or managed accounts, are man-



aged under the same trend following core system, though some may have investment constraints. Moreover, the portfolios may exhibit different target volatility levels, but this is not a problem since quantities move linearly with the leverage (and so with the target volatility). This execution dataset contains all the trades generated to implement the strategies, named parent orders, and the key characteristics of all child orders, such as an identifier, a date, the underlying futures, the quantity, the price, the broker it was sent to and the clearer. Thanks to the parent order identifier, we relate these trades to other relevant data, necessary to perform our trading cost analysis. Referential data contain the static characteristics of each futures, such as tick size, figure, the related market, the asset class. We also use information relative to the trading session, the model price, the used algorithm. The FX rate is given by the data provider and is necessary to calculate a global consistent price. Finally, some information coming from the firm middle office (such as AUM, broker, clearer and exchange fees) are gathered as well.

Tables 3.1 and 3.2 describe the parent orders, and decompose them across respectively time and space (asset classes). From a global point of view, the database contains around seventy thousand parent orders and 1.5 million child orders, spanned over nine years. The increase in the number of parent orders is in theory independent from the AUM, since a parent order contains all trades per day on a given futures contract. Each order represents on average close to 15 million dollars, though with a large time variation: from around 1 million in the first years to around 25-30 million dollars for the last three years. The first factor behind this is the increase in the AUM, which all things equal increase the quantity of all orders. The second factor is the leverage used by the manager to target the fund volatility. The increase in the number of child orders per parent, which measures the slicing intensity, is strong and close to the one observed on the average parent size. It is confirmed by a relatively stable size of child orders. The percentage of buy

Table 3.1 – Descriptive statistics about the structure of the parent orders in our dataset and its evolution over the years. *Note: Total traded size is the notional value of all traded parent orders, expressed in million dollars. The average parent size is the average notional value of the parent orders, expressed in million dollars. Each parent order is given a direction, which is common to all its child orders, and this information is defined at the parent order level. Each parent order can be sliced in child orders, so the average number of child orders and average size of each are two aspects of this slicing step and can be calculated.*

	# of Parent Orders (’000)	Total Traded Size (\$M)	Avg. Parent Size (\$M)	% Buy Orders	Avg. # of child orders per parent order	Avg. Child Size (\$M)
Overall	67.92	882 975.80	14.64	53.05	21.72	0.68
2010	0.23	314.60	1.36	46.55	1.08	1.25
2011	2.48	1 748.82	0.71	49.92	1.44	0.49
2012	3.41	2 927.23	0.86	53.82	1.81	0.47
2013	4.65	7 006.57	1.46	51.11	2.40	0.61
2014	6.25	37 401.25	5.93	57.30	7.98	0.74
2015	9.21	57 746.85	6.27	53.32	13.51	0.46
2016	9.91	65 350.68	6.59	51.86	12.66	0.52
2017	11.19	265 292.51	23.70	53.37	32.68	0.73
2018	11.97	388 424.54	32.45	49.14	39.28	0.83

orders stays close to 50% during the whole period.

From Table 3.2, interest rates futures are by far the most traded in terms of number of parent orders, and dollar value. The number is around ten times higher than the ones observed in energies or metals. This huge discrepancy has to be kept in mind when looking at the portfolio-level trading cost. It comes from the low volatility level observed in rates futures markets. Any significant position on these markets implies a high average parent order size. In addition, it seems that interest rates, bonds and currencies all exhibit a higher number of child orders per parent. This slicing feature of the algorithm on these asset classes matches the fact these markets have deep limit order books, which quickly replenish themselves. Liquidity aspects of each futures market can be taken into account in the execution algorithm. The buy percentage remains close to 50% across asset classes, with a small long bias

Table 3.2 – Descriptive statistics about the structure of the parent orders in our dataset and its decomposition across asset classes. *Note: Total traded size is the notional value of all traded parent orders, expressed in million dollars. The average parent size is the average notional value of the parent orders, expressed in million dollars. Each parent order is given a direction, which is common to all its child orders, and this information is defined at the parent order level. Each parent order can be sliced in child orders, so the average number of child orders and average size of each are two aspects of this slicing step and can be calculated.*

	# of Parent Orders (’000)	Total Traded Size (\$M)	Avg. Parent Size (\$M)	% Buy Orders	Avg. # of child orders per parent order	Avg. Child Size (\$M)
Overall	67.92	882 975.80	14.64	53.05	21.72	0.68
Agriculturals	6.94	4 994.97	0.79	48.13	15.06	0.05
Bonds	7.78	207 965.98	30.85	52.42	25.93	1.19
Equities	9.74	27 843.68	3.27	55.18	11.59	0.28
Energies	3.33	6 714.68	2.26	50.87	17.86	0.13
Metals	3.30	6 534.79	2.21	49.00	12.33	0.18
Interest Rates	31.53	599 572.28	22.06	54.05	26.14	0.84
Currencies	6.07	29 349.46	5.48	47.85	24.50	0.22

on equity and interest rates markets.

Tables 3.3 and 3.4 describe the size of parent orders, expressed as a traded quantity, and their participation rates in corresponding futures markets. About the evolution through time, parents orders have gone bigger, essentially due to the increase in the assets under management (AUM). However, it is difficult at this stage to interpret this evolution over time, as the average depends on the portfolio composition at each date. Indeed, the stated average volume is the average of the daily volume across all parent orders, so depend on the the markets traded on the corresponding period. The same goes for the average open interest. Only the calculations reported on Table 3.4 do not depend on the asset class weights within the portfolio.

The increase in the traded quantities seems more important than the one of the volume and open interest. Values of participation rates are relatively

Table 3.3 – Size of parent orders and their participation rate in futures markets, through time. *Note: Quantity is expressed as the number of lots of each parent order, and is compared to the daily market volume and open interest observed on that day. Then, values are averaged across parent orders. POV stands for Pourcentage of Volume, and POOI for Pourcentage of Open Interest. The POV (respectively POOI) is the ratio of the parent order total absolute quantity to the daily volume (resp. open interest) of the corresponding day.*

	Avg. Qty (#)	Avg. Volume (#)	Avg. Open Interest (OI) (#)	Avg. POV (bps)	Avg. POOI (bps)
2010	7.18	231 437.29	334 749.21	1.34	0.37
2011	3.83	209 969.67	559 350.44	2.09	0.20
2012	4.78	150 081.92	464 035.75	0.65	0.22
2013	7.48	171 005.67	498 429.28	1.13	0.27
2014	29.93	172 343.45	532 193.94	4.62	1.04
2015	35.27	170 689.21	540 680.32	5.83	1.28
2016	41.65	189 345.20	567 290.27	5.52	1.64
2017	136.20	184 968.56	620 821.77	18.16	4.73
2018	170.33	219 561.74	709 916.76	19.52	4.94

small, both considering volume and open interest. Indeed, the total trading of the asset manager only represents up to 20 basis points of the daily volume, with an overall overage of 11 basis points.

In Table 3.4, the asset class decomposition gives some insights regarding the futures market liquidity. Bonds and equities appear to be the most liquid ones, followed by interest rates which display a small volume in comparison to the open interest. The first asset class where futures trade, the agricultural markets, exhibits also this phenomenon. Both volume and open interest on currency futures are low, which appear as a surprise, since this asset class is the largest one in terms of total dollar volume across all currency contracts. This may be the result of a large portion of investors using forwards instead of futures. The participation rates of the trading of the studied money manager remain low across all asset classes.

Table 3.4 – Size of parent orders and their participation rate in futures markets, across asset classes. *Note: Quantity is expressed as the number of lots of each parent order, and is compared to the daily market volume and open interest observed on that day. Then, values are averaged across parent orders. POV stands for Pourcentage of Volume, and POOI for Pourcentage of Open Interest. The POV (respectively POOI) is the ratio of the parent order total absolute quantity to the daily volume (resp. open interest) of the corresponding day.*

	Avg. Qty (#)	Avg. Daily Volume (#)	Avg. Daily Open Interest (OI) (#)	Avg. POV (bps)	Avg. POOI (bps)
Agriculturals	29.60	64 652.56	236 469.03	7.26	2.40
Bonds	214.67	539 580.56	1 400 515.11	5.78	2.91
Equities	33.95	332 532.72	704 505.31	5.31	2.30
Energies	40.33	181 607.61	200 215.11	4.66	3.26
Metals	24.81	84 645.65	132 643.10	5.90	3.32
Interest Rates	89.84	117 417.84	633 842.44	15.43	1.91
Currencies	71.87	102 482.32	172 568.26	10.75	6.35

## 3.4 Results

We present in this section all the results obtained both at the individual trade level and at the fund level, i.e. including all the allocation decisions made by the manager to respect the funds' investment policy.

### 3.4.1 Execution costs at the trade level

Tables 3.5 and 3.6 report the Implementation Shortfall (IS) across time between 2012 and 2018 and across asset classes, along with standard proxies of liquidity such as tick size and volatility. Indeed, Kyle (1985) [69] (see also Bacry et al., 2015 [8], and Frazzini, Israel and Moskowitz, 2018 [45]) consider bid-ask spread and volatility as factors that explain market impact.<sup>3</sup> A first observation is related to the overall average implementation shortfall,

3. Results on IS for 2010 and 2011 are not reported as the number of trades is too small to ensure economic significance.

Table 3.5 – Yearly summary of the trade level Implementation Shortfall and related liquidity characteristics. *Note: Tick Size is calculated as the ratio of the tick to the parent order reference price and annual volatility corresponds to the volatility estimated over the year before the trade date of the corresponding parent order (for the corresponding futures market). Both averages are done across all relevant parent orders.*

	Avg. IS (bps)	Median IS (bps)	Avg. IS Sell (bps)	Avg. IS Buy (bps)	Avg. Tick Size (bps)	Avg. Annual Vol. (%)
Overall	1.29	0.34	1.38	1.21	4.03	7.97
2012	1.73	0.25	-0.09	3.29	3.45	7.65
2013	1.48	0.45	1.76	1.22	4.34	7.06
2014	1.51	0.46	1.80	1.30	4.32	6.21
2015	2.10	0.50	3.20	1.18	4.65	8.01
2016	1.03	0.34	1.80	0.36	4.01	9.29
2017	1.02	0.25	0.80	1.20	3.54	7.82
2018	1.47	0.34	1.63	1.30	3.70	7.46

which is of 1.29 basis points. This is much lower than what is observed in the equity cash market, where the implementation shortfall is around 15 basis points (as confirmed by Briere et al, 2019 [26] and Frazzini et al, 2018 [45]). Over the years, the average IS varies between 1.02 and 2.10 basis points. The median appears in every case except 2010 inferior to the mean, which is a sign of positive skewness: there are parent orders with very large implementation shortfalls. No specific pattern appears between the buy versus short side when comparing the average IS. Concerning the last three years of our sample, i.e. the period 2016-2018, we observe no specific upward trend in transaction costs, while trend following strategies exhibited negative performances. The result reported in Table 3.5 is the first confirmation that this disappointing performance is not related to a deterioration of the execution capability at the trade level. The use of IS allows to decompose the trading and zoom in on the trade level to obtain this result. The ability of the fund to access the futures market liquidity is not deteriorated even if the size of the fund increases a lot during the

Table 3.6 – Asset class summary of the trade level Implementation Shortfall and related liquidity characteristics. *Note: Tick Size is calculated as the ratio of the tick to the parent order reference price and annual volatility corresponds to the volatility estimated over the year before the trade date of the corresponding parent order (for the corresponding futures market). Both averages are done across all relevant parent orders.*

	Avg. IS (bps)	Median IS (bps)	Avg. IS Sell (bps)	Avg. IS Buy (bps)	Avg. Tick Size (bps)	Avg. Annual Vol. (%)
Overall	1.29	0.34	1.38	1.21	4.03	7.97
Agriculturals	4.62	3.82	4.38	4.88	3.93	21.50
Bonds	0.72	0.45	0.63	0.80	0.89	3.74
Equities	0.78	0.99	2.36	-0.49	1.09	14.46
Energies	3.26	2.79	0.94	5.48	1.60	29.84
Metals	4.30	3.25	4.20	4.40	1.47	19.35
Interest Rates	0.36	0.26	0.33	0.39	0.60	0.18
Currencies	0.99	0.70	0.78	1.22	33.06	9.06

period. Concerning the evolution of the average volatility, we observe this time a decrease, from 9.29% in 2016 to 7.46% in 2018. Considering equal quantities across asset classes, a decrease in volatility should be associated to a decrease in the implementation shortfall. Tables A15 and A16 in Appendix contain extremes quantiles of the IS distribution, through time and across asset classes. The 5% quantile is on every case below the 95% in absolute terms, confirming the right skewness.

We show in Table 3.6 that as expected, the implementation shortfall is the highest in commodity futures with a value five to ten times larger than in standard asset classes. This asset class displays both higher volatility and lower volume (on average). Looking at asset class decomposition, the number of parent orders seems to be out of phase from the average IS. These findings suggest the calculation of a quantity-weighted IS, or in other words, the total trading cost at the portfolio level.

Table 3.7 – Yearly decomposition of the aggregated (portfolio level) trading costs. *Note: Portfolio Trading Cost is the cost in dollars coming from the difference between the executed price and the model price, divided by the last AUM level to obtain a relative performance measure. Portfolio Fixed Cost is the explicit cost due to the commissions taken by the broker, the clearer and the exchange (also presented as relative to AUM). Portfolio Total Cost is the sum of these two costs.*

	Portfolio Trading Cost (%)	Portfolio Fixed Cost (%)	Portfolio Total Cost (%)
2012	3.06	0.63	3.69
2013	6.04	1.14	7.18
2014	4.49	0.82	5.31
2015	2.92	0.47	3.39
2016	1.25	0.41	1.66
2017	2.71	0.66	3.37
2018	3.45	0.65	4.10

### 3.4.2 Portfolio-level trading costs

Tables 3.7 and 3.8 report the total cost of trading, which is the sum of implicit (trading) and explicit (fixed) costs, decomposed across time and asset classes. The time-series variation of the annual trading cost is quite large, with almost a factor of five between the minimum and maximum, whereas the fixed cost is stable, around 70 basis points per year. The average annual total cost of trading is 3.20%. Surprisingly, the evolution of the portfolio trading cost does not match the one of the implementation shortfall. Indeed, high cost does not coincide with high implementation shortfall. The cost borne by the fund manager and the client is not fully reflected by the trade-by-trade implementation shortfall. Indeed, we observe a huge increase in the portfolio total cost between 2016 and 2018 while the IS on the same period remains stable. This result can explain the disappointing performance of trend following strategies in the 2016-2018 period. Part of the performance drop can indeed be explained by this increase of the transaction costs at the fund level, even if the execution quality remains stable. We have then to



Table 3.8 – Asset class decomposition of the aggregated (portfolio level) trading costs. *Note: Portfolio Trading Cost is the cost in dollars coming from the difference between the executed price and the model price, divided by the last AUM level to obtain a relative performance measure. Portfolio Fixed Cost is the explicit cost due to the commissions taken by the broker, the clearer and the exchange (also presented as relative to AUM). Portfolio Total Cost is the sum of these two costs.*

	Portfolio Trading Cost (%)	Portfolio Fixed Cost (%)	Portfolio Total Cost (%)
Agriculturals	1.66	0.39	2.05
Bonds	6.32	0.88	7.20
Equities	2.22	0.49	2.71
Energies	2.20	0.23	2.43
Metals	1.36	0.18	1.54
Interest Rates	11.60	2.69	14.29
Currencies	1.23	0.53	1.76

understand which mechanism is responsible for this phenomenon.

In terms of asset class repartition, we observe on Table 3.8 a similar disconnection between the individual level cost and the portfolio level cost. Agriculturals and metals have a high implementation shortfall on average, but are the sectors which contribute the less to the portfolio cost. Interest rates exhibit an average IS of 36 basis points (per trade) but is by far the largest contributor at the portfolio level, with a total cost of 11.60%. An indication of this difference comes from the fixed costs, due to their direct relation with the traded quantity. Commissions are different between futures, but overall this portfolio fixed cost increases as the traded quantity increases. The huge difference between interest rates and other asset classes fixed costs might be strongly explained by a difference in turnover.

### 3.4.3 Transaction costs, turnover and market conditions

The objective in this section is to explain the increase in the total trading cost of trend following, which essentially happened during the last three years. We include now all the information we have on the management decisions taken at the fund level. In particular, the leverage used to meet volatility objectives has an impact on the fund turnover and the transaction costs.

Turnover is the sum of traded quantities. The effect of the amount under management is linear with the target positions, and so on the turnover. A way to control for that is to calculate the turnover per million dollar traded, which is a relative measure of turnover. This feature of the trading seems to explain the time-series variation of the portfolio total trading cost, especially for the last three years. However, this correction is not perfect. Assuming the new money that recently flew into this asset management firm were under the lowest volatility program, the associated traded quantities would be much lower than the same amount managed at a higher volatility target. In other words, a portfolio targeting 20% volatility with 10 million dollars generates the same amount of trading that a portfolio targeting 5% volatility with 40 million dollars. To control for that, the assets under management of each portfolio must be rescaled each day to match a common volatility-equivalent AUM. Please refer to the appendix for the mathematics.

We also consider in this subsection the impact of market conditions on transaction costs. In addition to the average volatility indicator in the previous section, we define an average correlation indicator. A way to measure this "average correlation" between the traded assets is to consider a standard principal component analysis and evaluate the percentage of variance explained by the first axis. A high value indicates that all futures markets are actually much related to one factor, which is a linear combination

of them. Trend following strategies can be long or short any futures market, so a high negative correlation between futures should count as a high positive correlation. In addition to not being statistically meaningful, an average of the correlations would not capture this long/short issue. Trend following strategies are very often target volatility products. So, when the volatility of individual futures markets decrease, the fund manager mechanically has to increase the leverage to maintain the global exposure. Another potential source of turnover increase is the other factor influencing the portfolio volatility, namely the diversification. Indeed, a correlation decrease will reduce the portfolio volatility, so positions must be increased to reach the target volatility level. Let's look at the simple diversification mathematics. An equally-weighted long-only portfolio of  $N$  assets, with equal volatility  $\sigma_i$  and equal correlations  $\rho$ , has the following volatility:

$$\sigma_P = \sigma_i \sqrt{\frac{1 + (N - 1) \times \rho}{N}} \quad (3.8)$$

Table 3.9 – Total trading cost evolution and potential related features. *Note: Turnover is the total quantity (number of lots) traded. Adjusted Turnover is the quantity traded per amount of AUM, previously rescaled between portfolios to take into account their different volatility targets. The average explained variance is the yearly average of the pourcentage of variance explained by the first axis of a standard PCA, applied on the futures markets returns, and can be viewed as an "average correlation".*

	Portfolio Total Cost (%)	Turnover (#)	Adjusted Turnover ( $\frac{\#}{AUM}$ )	Avg. Annual Volatility (%)	Avg. Explained Variance (%)	SG Trend Annual Return (%)
2012	3.69	16 291	3 261.06	7.65	42.30	-3.52
2013	7.18	35 627	5 622.21	7.06	40.45	2.67
2014	5.32	185 065	5 049.62	6.21	26.41	19.70
2015	3.39	319 610	3 778.73	8.01	23.59	0.04
2016	1.66	402 384	3 729.89	9.29	29.15	-6.14
2017	3.37	1 512 247	5 820.92	7.82	27.68	2.20
2018	4.10	2 026 045	5 712.77	7.46	20.42	-8.11

Table 3.9 contains the total cost of trading, the raw and relative turnover measures, the market environment variables and the corresponding performance of the Société Générale Trend Index, which is the standard benchmark for trend following strategies. The turnover, expressed as the total quantity traded over the year, dramatically increases. However, this effect is mainly driven by the increase of the assets under management of the firm.

The phenomenon of volatility and correlations drop appears to be the reason of the increase in the adjusted turnover: the volatility gradually decreased from 9.29% to only 7.46% over these three years. In addition, our "average correlation" indicator exhibits a drastic decrease from 2016 to 2018, going from 29% to around 20%. Along with the drop in the markets' individual volatilities, a reduced correlation lowers the ex ante portfolio volatility, all other things equal. We are able to explain the increase in the adjusted turnover by a decrease in the volatility and in the homogeneity of the markets. We can proxy our dynamic strategy, which is long and short and with time-varying positions, to a long-only portfolio equally-invested across assets with the average volatility (equal weight feature) and percentage of explained variance (long-only feature) from Table 3.9. For 2016, a portfolio of 50 assets would exhibit an annual volatility of 5.02%, whereas in 2018, the same calculation would result in a 3.37 % annual volatility. Assuming a volatility target of 20%, we can imply that positions were leveraged by a factor 4 on average in 2016, whereas a factor 6 was needed to reach the target level in 2018. Finally, this 1.5 factor appears to fit well the variation observed in the adjusted turnover. From this, we can conclude that a very large portion (around 98%) of the increase in the adjusted turnover comes from the joint evolution of volatilities and correlations.

The performances of trend followers, as proxied by the SG Trend Index, were disappointing since 2015 in comparison to the long-term track record of this strategy. The average annual return of around -4% could be the result

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of the increase of trading costs. However, this is not the result of a worsen quality of trading but rather of an increase in the quantities traded, which itself is due to a decrease in the average volatility and correlations of futures markets.

Table A19 in Appendix gives additional insights regarding the asset-class decomposition of the yearly adjusted turnover, especially the high contribution of interest rates to cost is explained by their large preponderance in the portfolio adjusted turnover. This is also consistent with the interest rates having a much lower volatility than other markets (please refer to Table A20 in Appendix for the average yearly volatility per asset class).

### 3.4.4 Turnover and trends

It is well-known that equity momentum strategies generate large turnover, as shown amongst others by Korajczyk and Sadka (2004) [68], Barroso and Santa Clara (2015) [21], Frazzini et al. (2015) [44] and Briere et al. (2019) [26]. Since trend following or time-series momentum is also based on the momentum anomaly, one could argue the latter comes with high turnover as well. However, trend following is directional and trade futures, often less numerous than the single stocks belonging to an index. Both aspects may have an impact on the turnover. Baltas (2015) [15] analyzes the turnover of trend following strategies and finds it is three to five times larger than the one of a comparable long-only strategy. In a companion paper, Baltas and Kosowski (2013) [18] go one step further and study the relationship between turnover and portfolio features such as rebalancing frequency and holding period. The intuition is confirmed: daily reshuffling involves a turnover ten times larger than the one of the monthly reshuffled portfolio. The objective in this section is to explain the evolution of the turnover of trend following strategies by features that are specific to this strategy. We assume here that the turnover depends on the markets' trend quality (which is partly dependant on the

lookback period of the strategy) and on their cotrends. A ranging market, which keeps going up and down with very short trends (relative to the lookback horizon), thus misleads the trend follower who switches frequently his position, creating turnover. However, when a trend is continuing, the initial position is usually increased, which creates turnover. This turnover is the result of an improving trend quality at the individual market level. The mechanism through which the correlation between trends impacts the turnover is more difficult to grasp. In general, the portfolio direction (long or short) on a given market only depends on this futures market. However, this position may be reduced or increased if a cotrend risk is taken into account to assess the portfolio global risk, in a similar fashion as the diversification effect (due to the correlations) we documented in the previous section.

Based on Chevalier and Darolles (2019) [31] signature methodology, we extract the *signed* returns that will be used for both assessing the overall trending quality and calculating an average "cotrend" thanks to a standard PCA decomposition, as we did in the previous section.

Table 3.10 – Total trading cost evolution and trends' features. *Note: The average explained Signed variance is the yearly average of the pourcentage of variance explained by the first axis of a standard PCA, applied on the futures markets signed returns, which are obtained by applying the signature methodology on raw returns.*

	Adjusted Turnover ( $\frac{\#}{\text{AUM}}$ )	Avg. Trend Quality (%)	Avg. Explained <i>Signed</i> Variance (%)
2012	3 261.06	14.57	38.79
2013	5 622.21	12.82	39.39
2014	5 049.62	16.90	29.91
2015	3 778.73	22.40	33.61
2016	3 729.89	16.43	32.19
2017	5 820.92	14.45	37.02
2018	5 712.77	14.33	41.40

Table 3.10 reminds the yearly relative turnover, along with the contempo-

aneous average of both the trend quality and the percentage of explained signed variance, which we call an "average cotrend". It appears the turnover decreases as the quality of trends deteriorates. We can interpret this as the following fact: a trend continuation increases less the turnover than a change in the direction of the trend (long to short and vice-versa). Concerning the other market feature, it seems the more trends are correlated the higher the turnover. Further analysis is needed to better disentangle both effects.

### 3.5 Conclusion

With information on both trades and management decisions, we analyze the different sources of transaction costs. We show that the drop in the volatility of futures markets is the main factor explaining the relatively low performances of trend following strategies during the period starting from 2016 to 2018. In addition, specificities of the trend following strategies, such as markets trend quality and trend risk, influence the portfolio construction, and so the resulting turnover. We also show that the classic liquidity measures, such as bid-ask spread, do not give a good view on the effective transaction costs for a given strategy. All our analysis shows that it is essential to include in a transaction cost analysis some information regarding the fund management.

The next step of our analysis would be to use our dataset to calibrate a more general market impact model to allow some capacity calculation without any reference to a particular AUM historical path. This is left for future research.







# Conclusion générale

Mes travaux de thèse s'inscrivent dans le contexte de l'analyse de performance des hedge funds, et en particulier de ceux adoptant la stratégie de suivi de tendance. Ces fonds appartiennent à la catégorie de Commodity Trading Advisors (CTA), également appelés Managed Futures. Les fonds d'investissement alternatifs se distinguent de la gestion traditionnelle par leur sophistication, et attirent donc des investisseurs institutionnels. Une information symétrique est nécessaire pour que ce marché de la délégation de gestion fonctionne. Les modèles d'analyse de performance et de risque remplissent ce rôle, et permettent ainsi aux investisseurs de sélectionner les gérants qui leur conviennent.

La philosophie d'investissement des suiveurs de tendance consiste à investir sur les grandes classes d'actifs, au moyen de produits futures, en supposant que les tendances passées observées sur les prix vont continuer. Contrairement à de nombreuses stratégies hedge funds, la stratégie de trend following est directionnelle. Elle ne consiste pas à profiter d'un écart de prix entre deux actifs proches, appelé arbitrage, mais plutôt à prendre une position risquée sur des indices globaux de marché répartis sur toutes les principales classes d'actifs. De plus, ce modèle implique une remise en cause de l'hypothèse de marche aléatoire. A ce titre, les modèles d'évaluation traditionnellement appliqués aux fonds d'investissement alternatifs doivent être adaptés. Cette thèse vise justement à proposer de nouvelles méthodes

d'évaluation de la performance, dans le contexte des stratégies de suivi de tendance.

En s'appuyant sur la construction du time-series momentum et en l'étendant de sorte à extraire différents types de tendances présents sur les marchés financiers, la compréhension des stratégies CTA et Global Macro est améliorée. Nos résultats confirment que le profil de rendement-risque de la stratégie de suivi de tendance diffère de celui obtenu par des portefeuilles optionnels, approche de Fung et Hsieh (2001) [46] initialement suivie. De plus, nous qualifions cette stratégie d'anomalie puisque son profil est similaire à une assurance. Son skewness positif la distingue des stratégies d'arbitrage et primes de risque.

L'utilisation de la procédure de Bai Perron (1998) [10] dans un cadre multivarié permet de relier les marchés par l'angle des tendances communes. Le facteur extrait, représentant la partie systématique de ce risque, diffère du facteur de tendance développé au chapitre 1. Il est en effet présent au sein de styles de hedge funds différents de ceux exposés au TREND. Une première analyse le reliant au facteur de risque extrême de Bali (2014) [13] confirme la distinction entre stratégies convergentes et divergentes, entrevue au premier chapitre.

Le time-series momentum, ou notre facteur TREND, covarie avec les rendements des indices classiques des stratégies CTA. Cependant, ces derniers reflètent les performances réelles de fonds d'investissement. La performance de ces stratégies diffère de celle d'un facteur théorique par les coûts d'exécution. Ceux-ci s'avèrent importants et dépendants de l'environnement de marché. La liquidité des futures est confirmée mais les prises de décisions nécessaires au respect des objectifs de risque du fonds contrebalancent les faibles coûts d'exécution individuels. La qualité des tendances génère un turnover important, ce qui occasionne d'importants coûts de transaction finalement payés par les investisseurs. La réplification des indices CTA n'est donc pas chose

aisée. Ce travail soulève également des questions quant à l'inclusion de produits futures moins liquides dans les portefeuilles de suivi de tendance, et la scalabilité de ce type de stratégies.

Ma thèse contribue à la réduction de l'asymétrie d'information entre gérants et investisseurs, conséquence de la délégation de gestion. Le contexte spécifique des suiveurs de tendance revêt plusieurs paradoxes que je vise à clarifier. Le caractère purement systématique de cette stratégie ne s'accompagne pas d'une facilité d'explication de ses performances, comme en témoigne l'importante recherche à ce sujet. Les suiveurs de tendance ne cherchent pas à prédire le changement de tendance, rendant leurs rendements différents de ceux de portefeuilles optionnels et d'un facteur de cotendance parfait. Enfin, le fait d'intervenir sur des produits liquides tels que les futures n'implique pas un coût d'exécution faible. Les contraintes de risque au niveau du portefeuille imposent au gérant d'ajuster les leviers individuel et global générant d'importants coûts de trading, malgré une bonne qualité d'exécution par transaction.



# Annexes

## Annexe 1

Figure A1 – Track record of our *sector-TREND* factors. *Note: Log prices are displayed.*



Figure A2 – Track record of our *horizon-TREND* factors. *Note: Log prices are displayed.*

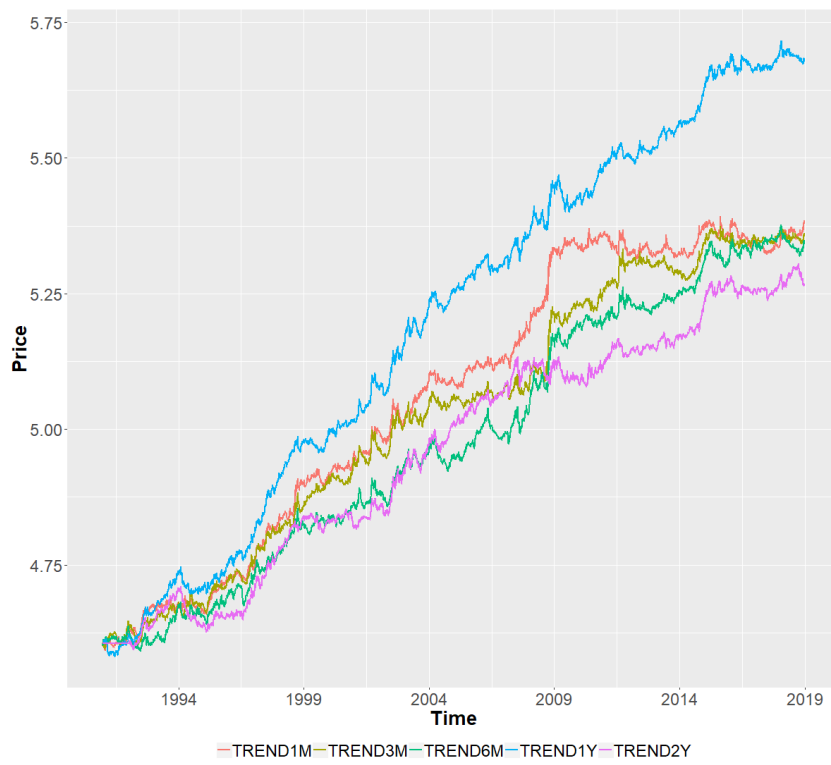


Table A1 – Main statistics of our monthly sector-TREND factors (gross of fees) over the global period. *Note: Calmar ratio is the ratio of the annual return to the maximum drawdown (MDD).*

	TREND	TRENDCOM	TRENDSTK	TRENDBD	TRENDFX
Ann. Ret. (in %)	11.62	7.65	6.01	9.78	4.973
Ann. Vol. (in %)	9.98	11.08	9.71	10.54	9.65
Sharpe Ratio ( $r_f = 0\%$ )	1.16	0.69	0.62	0.93	0.52
VaR (95%, in %)	1.16	0.69	0.62	0.93	0.52
MDD (in %)	-10.33	-21.47	-13.81	-13.24	-16.47
Calmar Ratio	1.12	0.36	0.44	0.74	0.30

Table A2 – Main statistics of our monthly horizon-TREND factors (gross of fees) over the global period. *Note: Calmar ratio is the ratio of the annual return to the maximum drawdown (MDD).*

	TREND1M	TREND3M	TREND6M	TREND1Y	TREND2Y	TRENDST	TRENDLT
Ann. Ret. (in %)	7.94	7.63	8.08	11.23	8.15	8.81	10.43
Ann. Vol. (in %)	9.31	9.74	9.90	9.79	9.74	9.68	9.71
Sharpe Ratio ( $r_f = 0\%$ )	0.85	0.78	0.82	1.15	0.84	0.91	1.07
VaR (95%, in %)	0.85	0.78	0.82	1.15	0.84	0.91	1.07
MDD (in %)	-13.71	-10.87	-14.78	-11.65	-19.51	-11.41	-13.01
Calmar Ratio	0.58	0.70	0.55	0.96	0.42	0.77	0.80





Table A4 – Pearson Correlation of HFR indexes and our TREND factors, on the FH sub-period running from January 2010 to March 2016.

	TREND	TRENDCOM	TRENDSTK	TRENDBD	TRENDFX	TRENDST	TRENDLT
Equity Market Neutral	-0.09	0.00	0.29	-0.43	-0.00	-0.34	0.10
Equity Quant. Directional	-0.06	-0.01	0.39	-0.44	-0.04	-0.28	0.09
Equity Short Selling	0.15	0.05	-0.40	0.57	0.08	0.24	0.06
Fund of funds	0.19	0.15	0.59	-0.37	0.14	-0.02	0.29
Systematic Diversified	0.85	0.56	0.40	0.47	0.60	0.70	0.78
Convertible Arbitrage	-0.11	0.01	0.33	-0.44	-0.15	-0.23	-0.04
Fixed Income Multistrat.	-0.03	-0.01	0.43	-0.37	-0.10	-0.13	0.03
Event-Driven	-0.15	-0.09	0.44	-0.54	-0.14	-0.29	-0.04
Equity Hedge	-0.15	-0.07	0.41	-0.53	-0.15	-0.31	-0.04
Global Macro	0.75	0.53	0.48	0.28	0.52	0.56	0.73
Relative Value	-0.17	-0.15	0.35	-0.41	-0.21	-0.29	-0.07

Table A5 – Regressions of the HFR indexes on the Fung-Hsieh factors, combined with TREND. T-statistic is displayed below the coefficients. *Note: Significant Trend exposures are in bold.*

	Alpha	PTFSBD	PTFSFX	PTFSCOM	PTFSIR	PTFSSTK	Equity	Size	Bond	Credit	TREND	R <sup>2</sup>
Eq. Market Neutral	0.00 (1.16)	-0.01 (-1.52)	0.00 (1.12)	-0.01 (-2.63)	-0.00 (-0.37)	-0.00 (-0.25)	0.12 (6.89)	0.00 (0.06)	0.02 (1.88)	0.00 (0.11)	0.02 (0.86)	0.69
Equity Quant. Dir.	-0.00 (-1.94)	-0.02 (-2.65)	0.01 (1.84)	-0.01 (-1.29)	0.00 (0.66)	-0.02 (-3.13)	0.41 (15.72)	0.07 (1.84)	0.01 (0.91)	0.02 (1.12)	<b>0.10</b> <b>(2.18)</b>	0.90
Equity Short Selling	-0.00 (-1.10)	0.02 (2.00)	-0.00 (-0.21)	-0.01 (-0.51)	-0.01 (-0.61)	-0.00 (-0.04)	-0.51 (-10.25)	-0.27 (-3.74)	-0.01 (-0.46)	0.05 (1.34)	-0.03 (-0.31)	0.83
Fund of funds	-0.00 (-1.59)	-0.00 (-0.91)	0.00 (0.61)	-0.00 (-0.63)	-0.00 (-0.48)	-0.00 (-0.75)	0.19 (8.85)	0.04 (1.17)	0.01 (1.14)	-0.04 (-2.35)	<b>0.17</b> <b>(4.88)</b>	0.79
Systematic Div.	-0.01 (-3.64)	0.00 (0.51)	0.01 (1.55)	0.01 (1.21)	0.00 (0.42)	-0.02 (-2.85)	0.17 (4.27)	-0.08 (-1.36)	-0.02 (-1.27)	0.01 (0.38)	<b>0.80</b> <b>(12.30)</b>	0.82
Convertible Arb.	0.00 (0.19)	-0.00 (-0.20)	0.00 (0.18)	-0.01 (-1.45)	-0.01 (-0.72)	-0.01 (-0.71)	0.21 (6.49)	0.04 (0.78)	-0.01 (-0.45)	-0.05 (-2.08)	0.02 (0.39)	0.64
Fixed Income Mult.	0.00 (2.05)	-0.01 (-1.73)	0.00 (0.91)	-0.00 (-0.85)	0.00 (0.36)	-0.00 (-0.93)	0.13 (5.28)	0.03 (0.91)	-0.02 (-1.63)	-0.07 (-3.85)	0.05 (1.16)	0.63
Event-Driven	-0.00 (-0.05)	-0.00 (-0.69)	0.00 (0.39)	-0.01 (-1.85)	-0.01 (-0.89)	-0.00 (-0.17)	0.27 (9.14)	0.08 (1.94)	0.00 (0.07)	-0.08 (-3.58)	0.00 (0.06)	0.81
Equity Hedge	-0.00 (-1.42)	-0.01 (-1.15)	0.01 (1.18)	-0.01 (-2.19)	-0.00 (-0.27)	-0.00 (-0.54)	0.44 (14.18)	0.15 (3.30)	0.00 (0.31)	-0.04 (-1.50)	-0.01 (-0.10)	0.89
Global Macro	-0.00 (-3.71)	-0.00 (-0.44)	0.01 (1.14)	0.00 (0.33)	0.00 (0.80)	-0.01 (-2.76)	0.15 (6.08)	-0.02 (-0.44)	-0.01 (-0.68)	0.00 (0.11)	<b>0.48</b> <b>(11.43)</b>	0.79
Relative Value	0.00 (2.22)	-0.01 (-1.20)	0.00 (0.20)	-0.01 (-1.16)	0.00 (0.01)	-0.01 (-2.01)	0.14 (6.05)	0.02 (0.71)	-0.02 (-1.67)	-0.07 (-3.79)	-0.00 (-0.11)	0.69

Figure A3 –  $R^2$  of two factor models (9- and 10-factor models) on selected HFR indexes. *Note: Red bars correspond to the Fung-Hsieh 9-factor model, and blue bars correspond to the 10-factor specification, which in addition contains the TREND factor.*

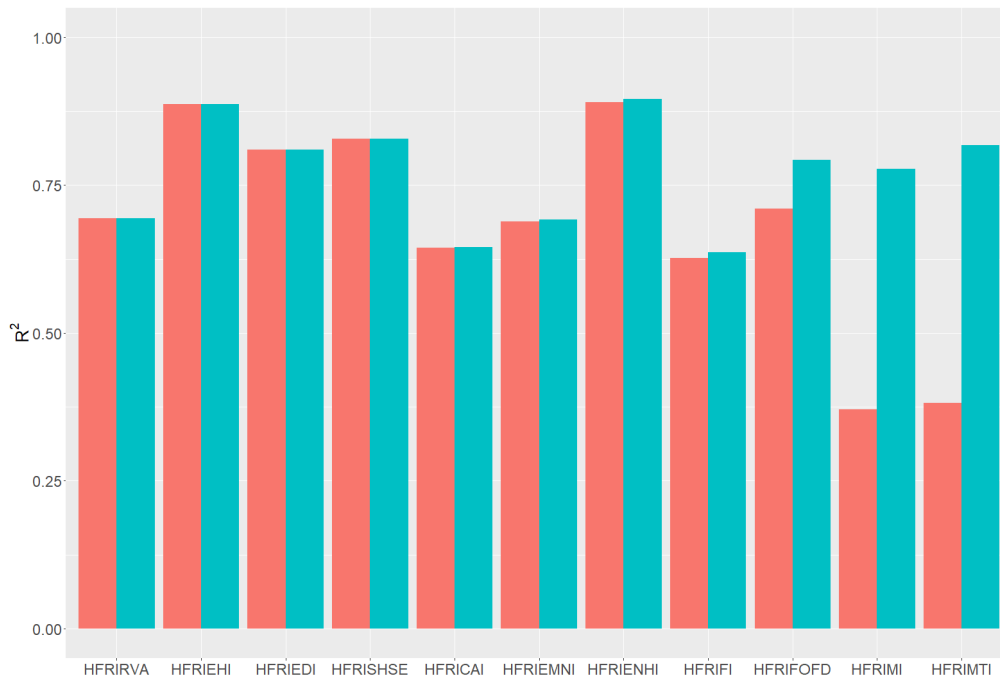


Table A6 – Regressions of the HFR indexes on the Fung-Hsieh factors, combined with the two horizon Trends. T-statistic is displayed below the coefficients. *Note: Only horizon Trend factors are displayed but the model used is the full one, with Fung-Hsieh nine factors.*

	TRENDST	TRENDLT	$R^2$
Equity Market Neutral	<b>-0.21</b> (-2.21)	<b>0.21</b> (2.81)	0.73
Equity Quant. Directional	-0.07 (-0.42)	<b>0.31</b> (2.6)	0.90
Equity Short Selling	<b>-0.61</b> (-2.07)	0.26 (1.13)	0.84
Fund of funds	0.25 (1.97)	<b>0.31</b> (3.17)	0.80
Systematic Diversified	<b>1.31</b> (5.62)	<b>1.23</b> (6.83)	0.82
Convertible Arbitrage	0.23 (1.18)	-0.12 (-0.79)	0.65
Fixed Income Multistrat.	0.27 (1.91)	-0.06 (-0.52)	0.65
Event-Driven	0.14 (0.79)	-0.06 (-0.41)	0.81
Equity Hedge	0.11 (0.58)	-0.08 (-0.53)	0.89
Global Macro	<b>0.79</b> (5.2)	<b>0.72</b> (6.17)	0.79
Relative Value	0.14 (1.02)	-0.09 (-0.83)	0.70

Table A7 – Description of the HFRI database.

HFRI Names	Strategies included
HFRI Macro: Systematic Diversified Index (HFRIMTI Index)	Managed Futures, Trend Following
HFRI EH: Equity Market Neutral Index (HFRIEMNI)	Quantitative Equity Market Neutral Strategies
HFRI EH: Quantitative Directional (HFRIENHI)	Factor-Based and Statistical Arbitrage Trading Strategies
HFRI FOF: Diversified Index (HFRIFOFD)	Investment in a variety of strategies among multiple managers
HFRI RV: Fixed Income-Convertible Arbitrage Index (HFRICAL)	Relative Value Strategies
HFRI RV: Multi-Strategy Index (HFRIFI)	Relative Value Strategies on Fixed Income
HFRI Event-Driven (Total) Index (HFRIEDI)	Event Driven Strategies
HFRI Equity Hedge (Total) Index (HFRIEHI)	Long-Short Equity Strategies
HFRI Macro (Total) Index (HFRIMI)	Global Macro Strategies
HFRI Relative Value (Total) Index (HFRIRVA)	Relative Value Strategies

Table A8 – Pearson Correlation of F&amp;H factors and TREND on a selection of 6 futures (S&amp;P500, US10Y T-note, EUR/USD, Corn, Gold and Crude Oil), on the FH sub-period running from January 2010 to March 2016.

	PTFSBD	PTFSFX	PTFSCOM	PTFSIR	PTFSSTK	Equity	Size	Bond	Credit	TRENDSEL
PTFSBD	1									
PTFSFX	0.5	1								
PTFSCOM	0.19	0.31	1							
PTFSIR	0.35	0.19	0.14	1						
PTFSSTK	0.31	0.28	0.23	0.23	1					
Equity	-0.51	-0.3	-0.22	-0.17	-0.25	1				
Size	-0.13	-0.03	-0.15	0.05	-0.02	0.36	1			
Bond	-0.34	-0.24	-0.25	-0.26	-0.17	0.4	0.37	1		
Credit	0.35	0.32	0.21	0.23	0.25	-0.38	-0.17	-0.55	1	
TRENDSEL	0.43	0.52	0.23	0.32	0.25	-0.13	0	-0.3	0.34	1

Table A9 – Pearson Correlation matrix of HFR indexes and TREND, on the period running from December 2010 to March 2016.

	TREND	HFRIMTI	HFRIMNI	HFRIMHI	HFRISHSE	HFRIFOFD	HFRICAI	HFRIFI	HFRIEDI	HFRIEHI	HFRIMI	HFRIRVA
TREND	1.00	0.45	0.14	-0.05	0.07	0.13	-0.11	-0.08	-0.11	-0.02	0.49	-0.16
HFRIMTI	0.45	1.00	0.23	0.54	-0.41	0.46	0.05	0.14	0.34	0.46	0.65	0.14
HFRIMNI	0.14	0.23	1.00	0.37	-0.18	0.48	0.36	0.41	0.48	0.52	0.34	0.46
HFRIMHI	-0.05	0.54	0.37	1.00	-0.86	0.77	0.46	0.59	0.83	0.91	0.53	0.61
HFRISHSE	0.07	-0.41	-0.18	-0.86	1.00	-0.59	-0.35	-0.45	-0.64	-0.78	-0.35	-0.44
HFRIFOFD	0.13	0.46	0.48	0.77	-0.59	1.00	0.58	0.74	0.81	0.84	0.69	0.72
HFRICAI	-0.11	0.05	0.36	0.46	-0.35	0.58	1.00	0.83	0.69	0.63	0.23	0.87
HFRIFI	-0.08	0.14	0.41	0.59	-0.45	0.74	0.83	1.00	0.79	0.71	0.39	0.86
HFRIEDI	-0.11	0.34	0.48	0.83	-0.64	0.81	0.69	0.79	1.00	0.88	0.49	0.83
HFRIEHI	-0.02	0.46	0.52	0.91	-0.78	0.84	0.63	0.71	0.88	1.00	0.53	0.74
HFRIMI	0.49	0.65	0.34	0.53	-0.35	0.69	0.23	0.39	0.49	0.53	1.00	0.32
HFRIRVA	-0.16	0.14	0.46	0.61	-0.44	0.72	0.87	0.86	0.83	0.74	0.32	1.00

Table A10 – Regressions of the HFR indexes on the Fung-Hsieh factors, combined with WML. *Note: Significant WML betas are in bold.*

	Alpha	PTFSBD	PTFSFX	PTFSCOM	PTFSIR	PTFSSTK	Equity	Size	Bond	Credit	WML	R <sup>2</sup>
Equity Market Neutral	0.00	-0.01	0.01	-0.01	-0.00	0.00	0.12	-0.01	0.01	-0.00	0.03	0.70
Equity Quant. Directional	-0.00	-0.01	0.01	-0.01	0.00	-0.02	0.42	0.05	0.01	0.01	0.03	0.89
Equity Short Selling	-0.00	0.03	-0.00	-0.00	-0.01	-0.01	-0.52	-0.26	-0.01	0.07	-0.08	0.84
Fund of funds	-0.00	0.00	0.01	-0.00	-0.00	-0.00	0.21	0.01	0.01	-0.06	0.02	0.71
Systematic Diversified	0.00	0.03	0.05	0.01	0.00	-0.01	0.25	-0.19	-0.05	-0.07	<b>0.15</b>	0.42
Convertible Arbitrage	0.00	0.00	0.00	-0.01	-0.01	-0.01	0.21	0.05	-0.00	-0.05	-0.06	0.66
Fixed Income Multistrat.	0.00	-0.01	0.01	-0.00	0.00	-0.01	0.13	0.03	-0.02	-0.07	-0.03	0.64
Event Driven	0.00	-0.00	0.00	-0.01	-0.01	-0.00	0.26	0.10	0.00	-0.07	<b>-0.07</b>	0.83
Equity Hedge	-0.00	-0.01	0.01	-0.01	-0.00	-0.01	0.44	0.17	0.01	-0.02	<b>-0.09</b>	0.90
Global Macro	-0.00	0.01	0.03	0.00	0.01	-0.01	0.20	-0.08	-0.02	-0.04	0.06	0.39
Relative Value	0.00	-0.01	0.00	-0.00	0.00	-0.01	0.13	0.03	-0.02	-0.06	<b>-0.06</b>	0.72

Annexes



Table A11 – Regressions of the HFR indexes on the Fung-Hsieh factors, combined with WML and TREND. *Note:* Significant WML and TREND betas are in bold.

	Alpha	PTFSBD	PTFSFX	PTFSCOM	PTFSIR	PTFSSTK	Equity	Size	Bond	Credit	WML	TREND	R <sup>2</sup>
Equity Market Neutral	0.00	-0.01	0.00	-0.01	-0.00	0.00	0.12	-0.01	0.01	-0.00	0.03	0.00	0.70
Equity Quant. Directional	-0.00	-0.02	0.01	-0.01	0.00	-0.02	0.42	0.07	0.01	0.02	0.02	0.03	0.90
Equity Short Selling	-0.00	0.02	-0.00	-0.00	-0.01	-0.01	-0.52	-0.25	-0.01	0.07	-0.08	0.00	0.84
Fund of funds	-0.00	-0.00	0.00	-0.00	-0.00	-0.00	0.19	0.04	0.01	-0.04	-0.02	<b>0.08</b>	0.79
Systematic Diversified	-0.01	0.00	0.02	0.01	0.00	-0.02	0.17	-0.07	-0.02	0.01	-0.00	<b>0.32</b>	0.82
Convertible Arbitrage	0.00	-0.00	0.00	-0.01	-0.00	-0.01	0.20	0.05	-0.00	-0.04	-0.07	0.02	0.67
Fixed Income Multistrat.	0.00	-0.01	0.00	-0.00	0.00	-0.01	0.12	0.05	-0.02	-0.07	-0.05	0.03	0.66
Event Driven	-0.00	-0.01	0.00	-0.01	-0.01	-0.01	0.25	0.10	0.01	-0.07	<b>-0.08</b>	0.02	0.83
Equity Hedge	-0.00	-0.01	0.01	-0.01	-0.00	-0.01	0.43	0.17	0.01	-0.02	<b>-0.10</b>	0.02	0.90
Global Macro	-0.00	-0.00	0.01	0.00	0.01	-0.02	0.15	-0.00	-0.00	0.01	-0.04	<b>0.20</b>	0.79
Relative Value	0.00	-0.01	-0.00	-0.00	0.00	-0.01	0.13	0.04	-0.01	-0.06	<b>-0.06</b>	0.01	0.72

## Annexe 2

### Drawdown anatomy test

Decomposition of the portfolio return across assets:

$$r_t^{Ptf} = \sum_i Contrib_t^i \quad (3.9)$$

- Choice of the window length:  $T$  days
- Block bootstrap:  $n = 10000$  blocks of length  $T$  and for each draw, observation of the number of negative contributors as well as the return of the portfolio. The block bootstrap procedure allows to keep the autocorrelation structure in the data.
- We draw a date (for example with a uniform distribution) and we calculate for each market  $i$  the global contribution over the period:  $\sum_{t=t_0}^{t=t_0+T} Contrib_t^i$ , and the portfolio performance over the same period:  $\sum_{t=t_0}^{t=t_0+T} r_t^{Ptf}$
- We form what we call the bootstrap matrix of dimension  $n * 2$ , which contains both information for each draw
- Calculation of the empirical probability of  $N = k$  negative contributors conditionally on the fact the return of the strategy is inferior to  $x\%$ . So we simply apply Bayes' formula on our bootstrap matrix:

$$P(N = k | r^{Ptf} < x) = \frac{P(N = k \cap r^{Ptf} < x)}{P(r^{Ptf} < x)} \quad (3.10)$$

where  $P$  is the empirical probability. In this case, empirical probability is the number of occurrence of the events divided by the number of draws.

- Calculation of the theoretical probability, under the hypothesis the  $T$ -days contributions follow a multivariate Gaussian distribution:

1. Estimation of both :
    - Marginal distribution
    - Conditional distribution
  2. Simulations and calculation of the 'empirical' (coming from the bootstrap) theoretical probability
  3. Comparison of both distributions
- A first statistic would be the simple difference between the conditional means:

$$E(N|r^{Ptf} < x) = \sum_k k * P(N = k|r^{Ptf} < x) \quad (3.11)$$

## Robustness tables and figures

Figure A4 –  $R^2$  of two factor models (9- and 10-factor models) on selected HFR indexes. Note: Red bars correspond to the Fung-Hsieh 9-factor model, and blue bars correspond to the 10-factor specification, which in addition contains the BREAKABS factor.

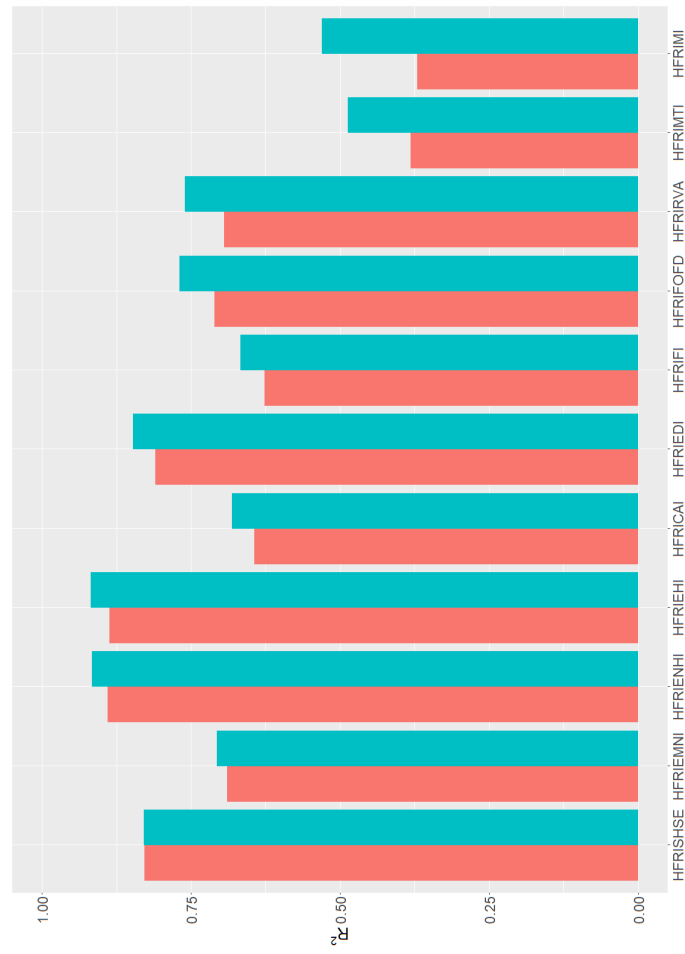


Table A12 – Regressions of the HFR indexes on the Fung-Hsieh factors, combined with BREAKABS. T-statistic is displayed below the coefficients. *Note: Significant BREAKABS exposures are in bold.*

	Alpha	PTFSBD	PTFSFX	PTFSCOM	PTFSIR	PTFSSTK	Equity	Size	Bond	Credit	F	R <sup>2</sup>
Equity Market Neutral	12.63	-0.01	0.01	-0.01	-0.00	0.00	0.08	-0.00	0.02	0.00	0.12	0.71
	1.86	-1.40	1.70	-2.30	-0.35	0.27	3.18	-0.01	2.44	0.34	1.95	
Equity Quant. Dir.	-6.94	-0.01	0.02	-0.00	0.00	-0.01	0.30	0.06	0.03	0.03	0.40	0.92
	-0.70	-2.47	3.40	-0.58	0.79	-2.16	8.13	1.86	2.39	1.69	4.48	
Equity Short Selling	-27.71	0.02	-0.00	-0.01	-0.01	-0.00	-0.49	-0.27	-0.01	0.05	-0.08	0.83
	-1.33	1.99	-0.37	-0.59	-0.62	-0.16	-6.38	-3.75	-0.56	1.30	-0.43	
Fund of funds	6.36	0.00	0.01	0.00	-0.00	0.00	0.10	0.02	0.03	-0.04	0.34	0.77
	0.69	0.22	2.79	0.22	-0.36	0.54	2.88	0.65	2.18	-2.21	4.05	
Systematic Diversified	23.70	0.03	0.05	0.02	0.01	-0.01	-0.04	-0.15	0.00	-0.01	0.89	0.49
	0.88	2.09	4.31	1.54	0.38	-0.35	-0.37	-1.63	0.13	-0.25	3.62	
Convertible Arbitrage	10.04	-0.00	0.00	-0.01	-0.01	-0.00	0.11	0.04	0.01	-0.04	0.32	0.68
	0.78	-0.14	0.48	-1.03	-0.74	-0.06	2.41	0.84	0.51	-1.73	2.74	
Fixed Income Mult.	29.80	-0.01	0.01	-0.00	0.00	-0.00	0.06	0.03	-0.01	-0.07	0.24	0.67
	3.11	-1.59	1.66	-0.37	0.41	-0.22	1.59	0.87	-0.68	-3.68	2.79	
Event-Driven	6.32	-0.01	0.00	-0.01	-0.01	0.00	0.14	0.09	0.02	-0.07	0.39	0.85
	0.58	-0.81	0.65	-1.36	-0.97	0.76	3.62	2.25	1.47	-3.24	3.95	
Equity Hedge	-11.39	-0.01	0.01	-0.01	-0.00	0.00	0.29	0.16	0.03	-0.02	0.50	0.92
	-1.03	-1.46	1.63	-1.70	-0.29	0.55	7.05	4.02	2.12	-0.81	4.96	
Global Macro	12.90	0.01	0.03	0.01	0.01	-0.00	-0.01	-0.06	0.02	-0.01	0.66	0.53
	0.83	1.52	4.26	1.22	0.67	-0.21	-0.18	-1.11	0.77	-0.24	4.67	
Relative Value	26.73	-0.01	0.00	-0.00	0.00	-0.01	0.04	0.03	-0.00	-0.06	0.32	0.76
	3.24	-1.46	0.35	-0.58	0.03	-1.22	1.22	0.91	-0.27	-3.44	4.20	

Table A13 – Regressions of the HFR indexes on the Fung-Hsieh factors, combined with DIV. T-statistic is displayed below the coefficients. *Note: Significant DIV exposures are in bold.*

	Alpha	PTFSBD	PTFSFX	PTFSCOM	PTFSIR	PTFSSTK	Equity	Size	Bond	Credit	DIV	R <sup>2</sup>
Equity Market Neutral	12.86	-0.01	0.01	-0.01	-0.00	0.00	0.09	-0.00	0.02	0.00	0.61	0.71
	1.89	-1.57	2.04	-2.57	-0.48	0.13	4.22	-0.12	2.42	0.22	1.97	
Equity Quant. Directional	-6.98	-0.02	0.02	-0.01	0.00	-0.01	0.34	0.06	0.03	0.03	1.82	0.91
	-0.68	-2.74	3.97	-1.13	0.51	-2.52	10.67	1.56	2.10	1.33	3.92	
Equity Short Selling	-27.29	0.02	-0.00	-0.01	-0.01	-0.00	-0.50	-0.27	-0.01	0.05	-0.26	0.83
	-1.31	2.00	-0.41	-0.53	-0.60	-0.10	-7.71	-3.72	-0.50	1.36	-0.27	
Fund of funds	4.71	-0.00	0.01	-0.00	-0.00	0.00	0.15	0.02	0.02	-0.05	1.11	0.74
	0.47	-0.01	2.97	-0.32	-0.50	0.02	4.97	0.43	1.52	-2.49	2.45	
Systematic Diversified	21.10	0.03	0.06	0.01	0.00	-0.01	0.09	-0.17	-0.01	-0.03	3.34	0.44
	0.75	1.76	4.50	1.02	0.19	-0.74	1.01	-1.73	-0.25	-0.57	2.60	
Convertible Arbitrage	11.20	-0.00	0.01	-0.01	-0.01	-0.00	0.13	0.03	0.01	-0.05	1.76	0.69
	0.88	-0.42	1.08	-1.39	-0.94	-0.22	3.38	0.67	0.55	-1.91	3.03	
Fixed Income Multistrat.	30.23	-0.01	0.01	-0.00	0.00	-0.00	0.08	0.02	-0.01	-0.07	1.22	0.67
	3.15	-1.84	2.16	-0.72	0.23	-0.42	2.56	0.70	-0.74	-3.89	2.78	
Event-Driven	6.71	-0.01	0.01	-0.01	-0.01	0.00	0.18	0.08	0.02	-0.07	1.88	0.84
	0.61	-1.14	1.35	-1.86	-1.20	0.45	5.30	2.01	1.33	-3.50	3.75	
Equity Hedge	-10.27	-0.01	0.01	-0.01	-0.00	0.00	0.33	0.14	0.03	-0.02	2.57	0.92
	-0.93	-1.93	2.61	-2.35	-0.62	0.21	9.54	3.76	2.09	-1.12	5.12	
Global Macro	11.55	0.01	0.04	0.00	0.00	-0.01	0.08	-0.07	0.01	-0.02	2.65	0.47
	0.70	1.11	4.57	0.58	0.40	-0.68	1.48	-1.27	0.34	-0.62	3.50	
Relative Value	27.05	-0.01	0.00	-0.00	-0.00	-0.01	0.07	0.02	-0.00	-0.06	1.52	0.75
	3.23	-1.80	1.11	-1.11	-0.23	-1.56	2.57	0.66	-0.41	-3.72	3.98	

Figure A5 –  $R^2$  of two factor models (9- and 10-factor models) on selected HFR indexes. Note: Red bars correspond to the Fung-Hsieh 9-factor model, and blue bars correspond to the 10-factor specification, which in addition contains the DIV factor.

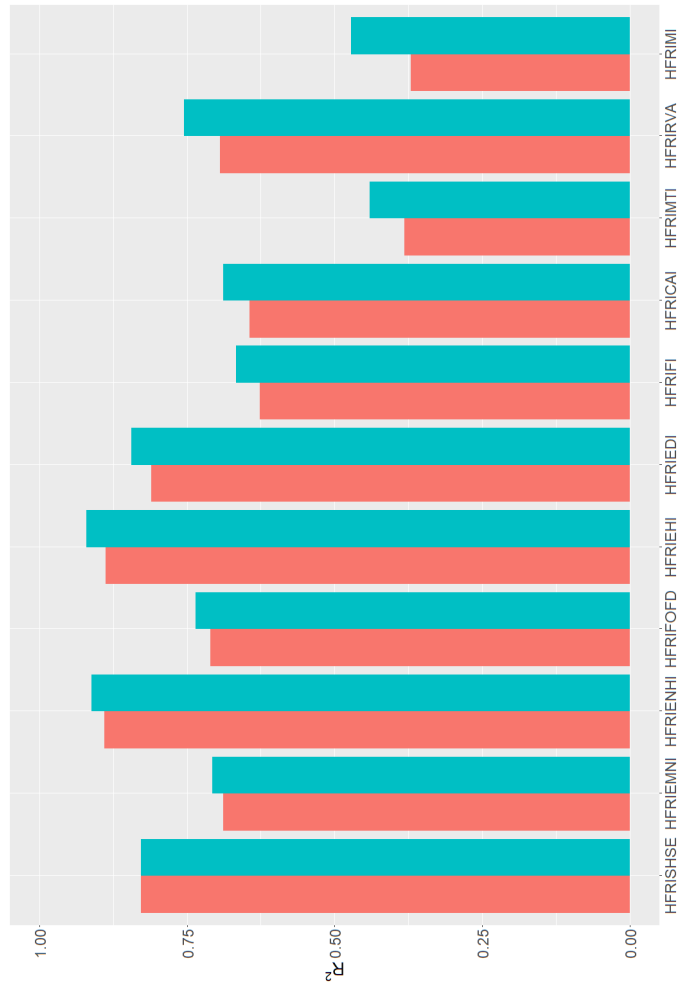
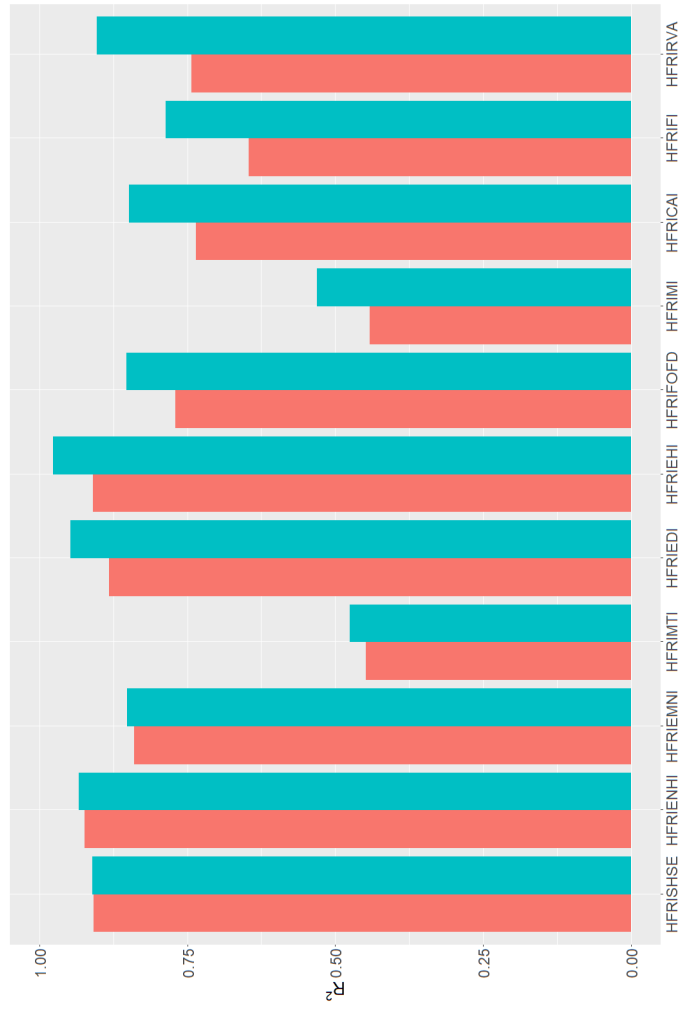


Table A14 – Regressions of the HFR indexes on the Fung-Hsieh factors, combined with TAIL. T-statistic is displayed below the coefficients. *Note: Significant TAIL exposures are in bold.*

	Alpha	PTFSBD	PTFSFX	PTFSCOM	PTFSIR	PTFSSTK	Equity	Size	Bond	Credit	TAIL	R <sup>2</sup>
Equity Market Neutral	-5.35	-0.00	0.01	-0.01	0.01	-0.01	0.08	0.04	0.01	0.00	0.07	0.85
	-0.51	-0.57	1.33	-1.32	1.07	-2.24	2.07	0.89	0.91	0.08	1.42	
Equity Quant. Directional	-13.53	-0.01	0.02	-0.01	0.02	-0.03	0.32	0.03	0.02	0.02	0.18	0.93
	-0.73	-1.52	2.49	-0.91	1.99	-2.18	4.92	0.43	0.65	0.53	1.97	
Equity Short Selling	-64.20	0.03	-0.01	-0.00	-0.01	-0.02	-0.44	-0.33	-0.00	0.06	-0.13	0.91
	-2.06	1.95	-0.53	-0.17	-0.29	-1.05	-4.00	-2.48	-0.04	1.13	-0.85	
Fund of funds	12.97	0.00	0.01	0.01	0.01	-0.01	0.02	-0.07	0.03	-0.04	0.25	0.85
	0.95	0.62	1.14	1.41	0.75	-0.93	0.36	-1.20	1.69	-1.82	3.76	
Systematic Diversified	51.88	0.06	0.04	0.06	-0.00	0.01	0.10	-0.32	0.06	-0.03	0.29	0.48
	1.00	2.17	1.55	1.62	-0.06	0.17	0.52	-1.41	0.81	-0.29	1.14	
Convertible Arbitrage	12.72	0.01	0.00	0.00	0.00	-0.02	0.03	-0.13	0.01	-0.03	0.41	0.85
	0.65	0.79	0.50	0.24	0.04	-1.64	0.47	-1.60	0.31	-0.86	4.31	
Fixed Income Multistrat.	42.96	-0.01	0.00	0.02	0.01	-0.01	-0.07	-0.09	-0.00	-0.07	0.31	0.79
	2.77	-1.40	0.50	1.48	0.70	-0.69	-1.23	-1.34	-0.10	-2.50	4.05	
Event-Driven	28.11	-0.01	0.01	-0.00	0.00	-0.01	0.05	-0.02	0.02	-0.06	0.34	0.95
	2.29	-0.87	1.81	-0.56	0.52	-1.21	1.13	-0.38	1.26	-2.62	5.59	
Equity Hedge	-5.27	-0.00	0.01	-0.00	0.01	-0.01	0.15	-0.01	0.03	-0.01	0.51	0.98
	-0.44	-0.07	1.12	-0.36	1.59	-1.30	3.59	-0.12	1.80	-0.26	8.62	
Global Macro	30.61	0.03	0.01	0.04	0.00	0.00	0.03	-0.17	0.05	-0.01	0.33	0.53
	0.99	2.16	1.02	1.81	0.29	0.01	0.23	-1.26	1.06	-0.15	2.18	
Relative Value	44.41	-0.00	-0.00	0.01	0.01	-0.02	-0.07	-0.09	0.01	-0.03	0.30	0.90
	4.59	-0.99	-0.41	1.63	1.43	-3.22	-2.09	-2.26	0.98	-1.86	6.41	



Figure A6 –  $R^2$  of two factor models (9- and 10-factor models) on selected HFR indexes. Note: Red bars correspond to the Fung-Hsieh 9-factor model, and blue bars correspond to the 10-factor specification, which in addition contains the TAIL factor.



## Annexe 3

### Implementation Shortfall distribution

Table A15 – Extremes quantiles of the IS distribution, through time.

	$q_5(IS)$ (bps)	$q_{95}(IS)$ (bps)
Overall	33.63	-28.46
2010	38.63	-47.86
2011	39.13	-40.26
2012	26.86	-20.86
2013	30.83	-22.78
2014	33.40	-23.46
2015	44.93	-39.33
2016	37.40	-31.48
2017	32.35	-28.04
2018	32.41	-26.00

Table A16 – Extremes quantiles of the IS distribution, across asset classes.

	$q_5(IS)$ (bps)	$q_{95}(IS)$ (bps)
Overall	33.63	-28.46
Agriculturals	75.17	-65.81
Bonds	13.20	-10.90
Equities	41.10	-39.80
Energies	98.47	-86.62
Metals	56.36	-44.65
Interest Rates	1.51	-0.53
Currencies	25.10	-22.01

Figure A7 – Asset Class distribution of the implementation shortfall.

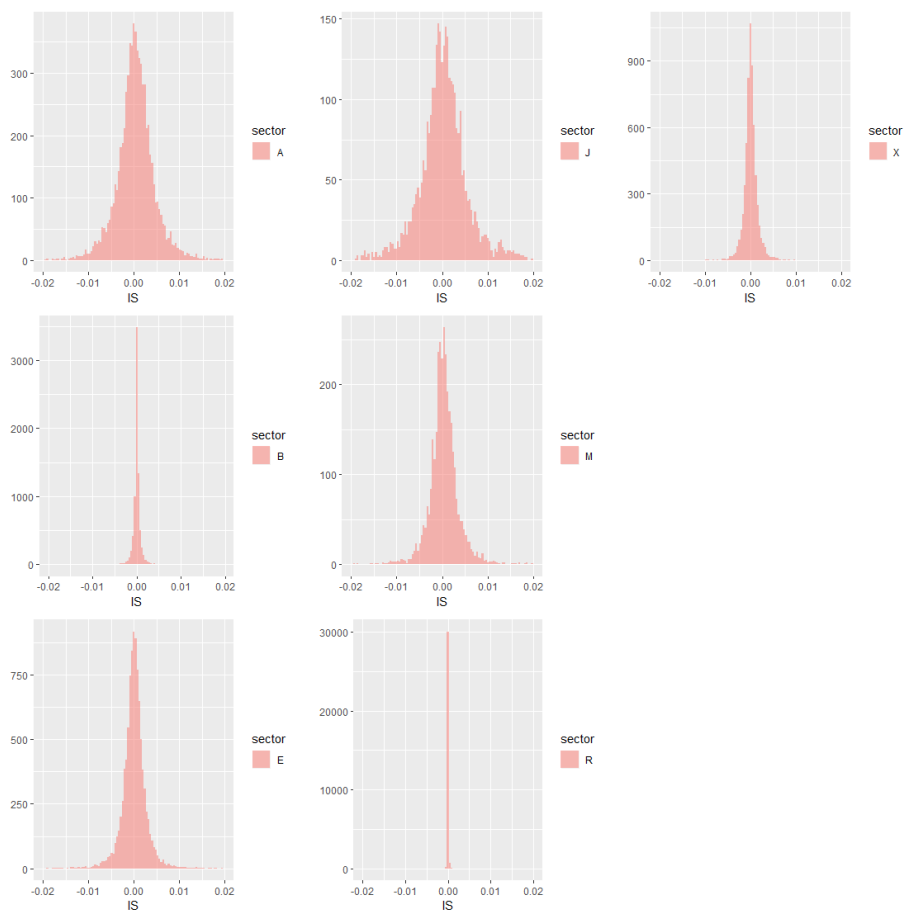


Figure A8 – Asset Class distribution of the volatility-adjusted implementation shortfall. *Note: The volatility we use here corresponds to the volatility estimated over the year before the trade date of the corresponding parent order, for the corresponding futures market.*

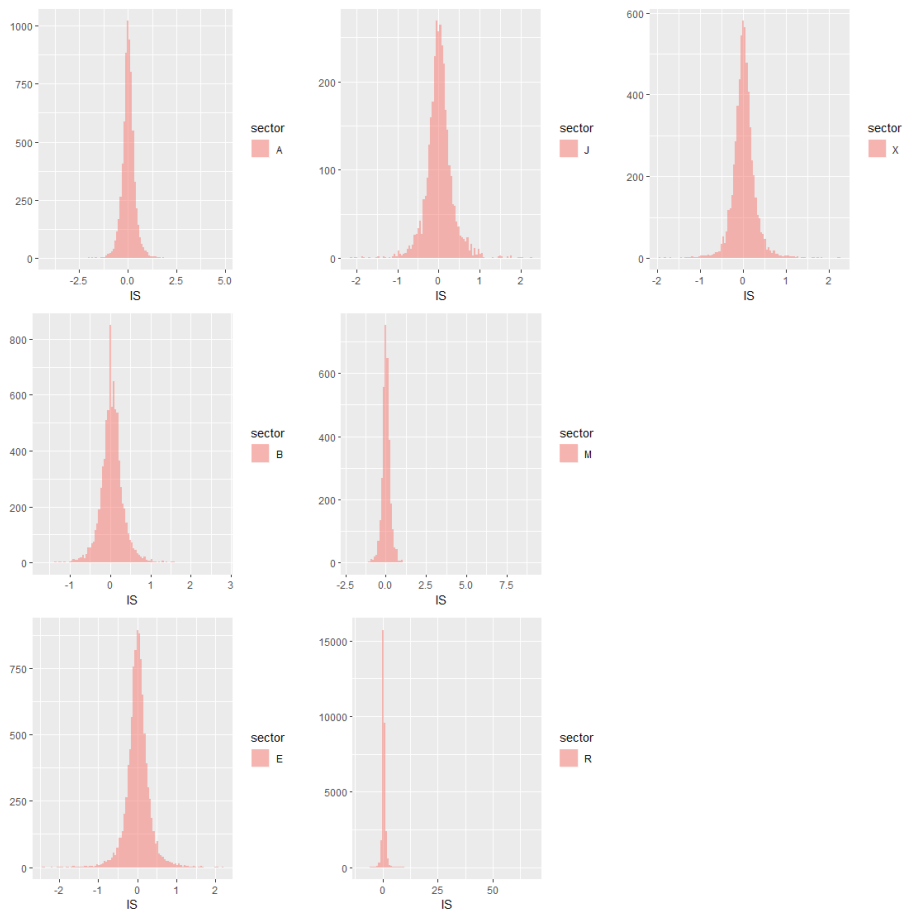


Table A17 – Additional description of the implementation shortfall, per year. Note: The tick-adjusted IS is the slippage (difference between model price and executed price) expressed as a number of ticks. The vol-adjusted IS is the standard IS, expressed as a number of daily volatilities.

	Avg. IS (bps)	Avg. Tick- adjusted IS (#ticks)	Avg. Vol (%)	Avg. Vol- adjusted IS (# vol.)	Median IS (bps)	Median Tick- adjusted IS (#ticks)	Median Vol (%)	Median Vol-adjusted IS (# vol.)
2010	-0.45	-0.06	16.22	0.03	0.42	0.02	14.40	0.00
2011	0.24	-0.12	9.28	0.09	0.00	0.00	0.79	0.00
2012	1.73	1.49	7.65	0.11	0.25	0.09	0.46	0.02
2013	1.48	1.54	7.06	0.15	0.45	0.30	0.71	0.03
2014	1.51	1.76	6.21	0.22	0.46	0.50	0.59	0.06
2015	2.10	1.37	8.01	0.28	0.50	0.78	0.32	0.10
2016	1.03	0.88	9.29	0.18	0.34	0.50	1.68	0.05
2017	1.02	0.89	7.82	0.22	0.25	0.33	4.12	0.05
2018	1.47	1.66	7.46	0.22	0.34	0.50	4.00	0.07
2019	0.75	0.93	8.59	0.16	0.34	0.41	5.47	0.05

Table A18 – Additional description of the implementation shortfall, across asset classes. *Note: The tick-adjusted IS is the slippage (difference between model price and executed price) expressed as a number of ticks. The vol-adjusted IS is the standard IS, expressed as a number of daily volatilities.*

	Avg. IS (bps)	Avg. Tick- adjusted IS (#ticks)	Avg. Vol (%)	Avg. Vol- adj. IS (# vol.)	Median IS (bps)	Median Tick-adj. IS (#ticks)	Median Vol (%)	Median Vol-adj. IS (# vol.)
Ags.	4.62	1.33	21.50	0.03	3.82	1.00	20.56	0.03
Bonds	0.72	0.78	3.74	0.04	0.45	0.71	3.71	0.04
Equities	0.78	1.03	14.46	0.01	0.99	1.00	13.50	0.01
Energies	3.26	4.02	29.84	0.02	2.79	2.00	28.92	0.02
Metals	4.30	5.32	19.35	0.03	3.25	2.33	18.87	0.03
Rates	0.36	0.70	0.18	0.40	0.26	0.50	0.17	0.25
FX	0.99	0.68	9.06	0.02	0.70	0.02	8.45	0.01

## Focus on costs features

Table A19 – Relative Turnover (#/ million \$) decomposed across years and asset classes. *Note: The relative turnover is the yearly sum across all relevant parent orders, of the absolute traded quantity divided by the firm volatility-adjusted AUM.*

	Ags.	Bonds	Equities	Energies	Metals	Interest Rates	Currencies	Total
2010	12.86	51.64	23.46	13.16	8.36	206.15	22.46	338.10
2011	49.65	364.35	129.50	81.67	39.69	811.33	143.41	1 619.59
2012	109.77	1 100.46	203.35	118.66	59.96	1 416.46	252.39	3 261.06
2013	212.97	1 564.59	366.42	114.96	69.12	2 968.22	325.93	5 622.21
2014	154.85	1 307.77	324.49	120.41	65.57	2 730.21	346.31	5 049.62
2015	95.62	1 257.69	181.45	80.77	46.54	1 855.36	261.30	3 778.73
2016	110.00	1 486.45	224.72	66.95	48.54	1 488.13	305.10	3 729.89
2017	185.01	1 582.03	434.56	126.55	76.10	3 023.87	392.80	5 820.92
2018	204.43	1 699.49	280.93	154.43	90.58	2 881.53	401.37	5 712.77

Table A20 – Average Annualized Volatility decomposed across years and asset classes. *Note: The average volatility is calculated across all relevant parent orders, whose daily volatility is the past one year estimate.*

	Ags.	Bonds	Equities	Energies	Metals	Interest Rates	Currencies	Overall
2010	28.02	5.30	18.22	31.55	24.68	0.33	11.24	16.22
2011	28.55	4.68	19.21	29.57	26.09	0.32	11.43	9.28
2012	26.22	4.38	19.60	28.93	25.10	0.33	9.88	7.65
2013	20.24	3.79	13.96	23.85	22.19	0.20	8.62	7.12
2014	19.76	3.44	12.02	20.40	17.38	0.15	6.96	6.20
2015	22.07	4.15	16.86	33.14	19.53	0.14	10.45	8.01
2016	22.47	4.42	18.45	41.40	22.25	0.19	11.24	9.29
2017	21.93	3.79	11.32	30.50	19.00	0.15	9.51	7.82
2018	20.45	3.14	11.96	25.32	16.85	0.16	8.06	7.46

## Relative Turnover

The raw turnover writes:

$$\text{Turnover}_t = \sum_m Q_m \quad (3.12)$$

The turnover per million dollars is:

$$\text{Relative Turnover}_t = \sum_m \frac{Q_m}{\text{AUM}_t} \quad (3.13)$$

where  $\text{AUM}_t$  is the total assets under management (in dollars) at date  $t$  managed by the firm. Assume the following decomposition across portfolios:

$$\text{AUM}_t = \sum_p \text{AUM}_t^p \quad (3.14)$$

Each portfolio  $p$  is managed at target volatility  $\sigma_p$ . Its actual aum value  $\text{AUM}_t^p$  is equivalent to the following value of AUM managed at the volatility  $\sigma_{\text{ref}}$ :  $\text{AUM}_t^p \times \frac{\sigma_p}{\sigma_{\text{ref}}}$ . The total rescaled AUM writes:

$$\text{A}\tilde{\text{U}}\text{M}_t = \sum_p \text{AUM}_t^p \times \frac{\sigma_p}{\sigma_{\text{ref}}} \quad (3.15)$$

Finally, the volatility-adjusted version of the turnover per million dollars is:

$$\text{Relative Turnover}_t^{\text{ref}} = \sum_m \frac{Q_m}{\text{A}\tilde{\text{U}}\text{M}_t} \quad (3.16)$$



## Capacity simulation

### Mathematics

The estimated portfolio fixed cost (EFC) writes:

$$\begin{aligned} \text{EFC} &= \frac{\sum_m \tilde{Q}_m \times (\text{BrokerageFee} + \text{ClearingFee} + \text{ExchangeFee})}{\text{AUM}_{\text{target}}} \\ &= \frac{\sum_{m \in t} Q_m \times \frac{\text{AUM}_{\text{target}}}{\text{AUM}_m} \times (\text{BrokerageFee} + \text{ClearingFee} + \text{ExchangeFee})}{\text{AUM}_{\text{target}}} \\ &= \frac{\sum_{m \in t} Q_m \times (\text{BrokerageFee} + \text{ClearingFee} + \text{ExchangeFee})}{\text{AUM}_m} \\ &= \text{Portfolio Fixed Cost} \end{aligned} \tag{3.17}$$

### Approach and results

This section aims at estimating the total trading cost at different levels of assets under management. This simulation would allow to assess the total capacity of a trend following strategy. Instead of estimating the cost through an analysis of parent orders, we will use the composition of the child orders and their partial implementation shortfall to calculate the theoretical cost one would pay when executing a smaller total quantity. Essentially, we are going to estimate a function linking the AUM and the related trading cost in the neighbourhood of the maximum AUM of the management firm. We will then extend this function for higher values of AUM.

The procedure is as follows. A level of AUM is fixed,  $\text{AUM}_{\text{Target}}$ , (lower than the maximum observed) and we filter in all parent orders that happened a day where the AUM was higher than the fixed level. The total quantity  $Q_m$  is then rescaled to get the total quantity that would have been traded if

the AUM was at the target level:

$$\tilde{Q}_m = Q_m \times \frac{\text{AUM}_{\text{Target}}}{\text{AUM}_m}. \quad (3.18)$$

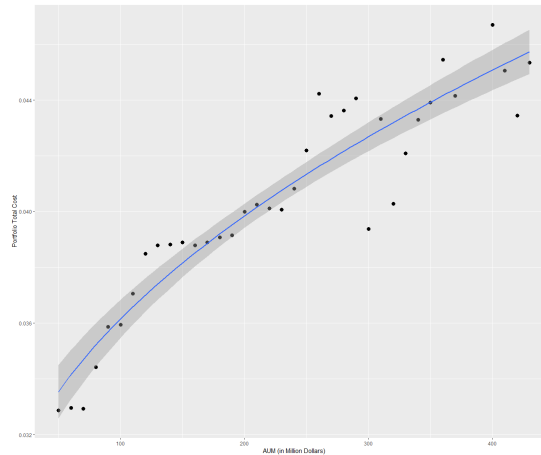
Due to our filter, we necessarily have  $\text{AUM}_{\text{target}} \leq \text{AUM}_m$ , so  $\tilde{Q}_m \leq Q_m$ . Then, for each parent order, we identify the child order that allows to reach a total traded quantity of at least  $\tilde{Q}_m$  and we take the corresponding average executed price as the theoretical price one would have got, noted  $\tilde{P}_m^{\text{exec}} = \frac{\sum_{i=1}^k p_i * q_i}{\sum_{i=1}^k q_i}$ , with  $k = \min\{c / \sum_{j=1}^c q_j \geq \tilde{Q}_m\}$ .

We can calculate now the trading cost, considering both our theoretical quantity and theoretical fill price. These are called theoretical because of the assumption of a lowered AUM, but parent orders went exactly through these levels at one point during the day so these prices are nonetheless realistic. Then, we aggregate the trading cost across the filtered set of parent orders. To get a yearly total cost, the cost must be rescaled via an estimation of the number of days in a year and the number of days in the filtered set,  $N_S$ . The final estimated yearly cost (E $\hat{\text{TC}}$ ) writes:

$$\text{E}\hat{\text{TC}}(\text{AUM}_{\text{Target}}) = \frac{\sum_{m \in S} \tilde{Q}_m \times S_m \times \left( \tilde{P}_m^{\text{exec}} - P_m^{\text{ref}} \right)}{\text{AUM}_{\text{Target}}} \times \frac{N_S}{260}. \quad (3.19)$$

The portfolio fixed cost should also be reassessed at the theoretical AUM level. However, these commissions are fixed and only depend on the quantity. When writing this cost as a performance, in other terms relative to the AUM level, the linear change in the AUM is balanced by the same change in the quantity, making the ratio constant. To avoid depending on the costs over one year, which is related to the trading of futures over this particular year, we will use the whole sample as a global estimation of the average trading, in terms of futures market repartition. The estimated annual fixed cost is

Figure A9 – Estimated yearly trading cost and the corresponding theoretical AUM level.



0.66%.

Figure A9 displays the AUM level we set at the beginning of the procedure and the corresponding trading cost we would have got, had we filled lower trading quantities. In order to predict potential trading cost at larger AUM, we estimated the following linear model thanks to the standard OLS estimator:

$$\text{Cost} = \alpha + \beta \times \sqrt{\text{AUM}} + \epsilon \quad (3.20)$$

Since there is no cost associated with a null AUM, there should be a non-continuity on the positive side of 0 which would make the model misspecified on this part. Our model does not suffer from that since we start with an AUM of 50 million dollars. We interpret the intercept as the following: it is the cost that comes with executing orders once one starts trading, say with a \$1M AUM. We estimate it at around 2.72%. The beta coefficient of the regression, interpreted as the marginal cost related to managing an additional million dollars, is estimated at 8.92 basis points. The  $R^2$  of the regression is 88.3%. With strong and complex assumptions regarding the liquidity of the markets, the structure of their order books, and the trading turnover

of a trend following strategy, we are able to estimate the cost of managing an extra million dollars which gives insights regarding the capacity of these strategies. Trend following strategies, as proxied by the SG Trend Index, exhibit a 0.4 net Sharpe Ratio since 2000. At a target volatility of 20%, it is equivalent to delivering an annual return of 8%. The AUM that would bring the total trading cost to the level of the net-of-fees performance, called breakeven AUM, is \$3 500M.



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## RÉSUMÉ

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Les stratégies de suivi de tendance ont rencontré ces dernières années un fort d'intérêt de la part des investisseurs institutionnels, du fait notamment de leur bonne performance lors de la crise économique et financière de 2008. Les années 2016 à 2018 ont rebattu les cartes, avec des performances jugées mauvaises par de nombreux clients. Cette thèse s'intéresse aux différentes caractéristiques des stratégies de suivi de tendance que sont la performance, le risque et les coûts d'exécution, et propose de nouvelles manières d'aborder ces sujets. Le chapitre 1 explique la différence de performance entre les styles de hedge funds en confirmant la présence de tendances au sein des stratégies CTA et Global Macro. Le caractère assurantiel de cette stratégie est confirmé au sein de tous les types de hedge funds. Le chapitre 2 propose une nouvelle décomposition du risque associée aux stratégies de suivi de tendance en une composante commune et une composante spécifique. L'extraction d'un facteur de risque systématique et son ajout aux modèles factoriels standards permettent de mieux expliquer les performances des styles de hedge funds, et ce de manière différente du chapitre 1. Enfin, le chapitre 3 aborde la question de l'exécution d'une stratégie de suivi de tendance. Le coût payé par l'investisseur, c'est-à-dire le coût associé à la gestion du portefeuille, n'est pas seulement fonction de la liquidité individuelle des actifs traités mais dépend également des décisions d'allocation prises par le gérant pour satisfaire aux objectifs de performance et de risque du fonds.

## MOTS CLÉS

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suivi de tendance, fonds d'investissements, construction de portefeuille, liquidité

## ABSTRACT

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Trend-following strategies became increasingly popular among institutional investors after exhibiting good performances during the 2008 global financial crisis. The 2016-2018 years reshuffled the cards due to disappointing performances. This thesis focuses on the different characteristics of the performances of trend following strategies, namely performance, risk and execution, and proposes new ways of analyzing them. Chapter 1 explains the differences in performance across hedge fund styles by confirming trends are harvested among CTA and Macro strategies. A trend exposure is shown to resemble insurance among all kinds of hedge funds. Chapter 2 proposes a break risk decomposition adapted to trend following strategies into systematic and specific components. The extracted systematic risk factor helps understanding hedge fund styles that were not exposed to the chapter 1 factor. This chapter paves the way for the construction of smart trend indices. Finally, Chapter 3 discusses the cost of implementing such strategy. The cost paid by the investor, which is the total implementation cost of the portfolio, is not only a function of the individual liquidity of traded assets, as measured by the trade-by-trade execution cost. This total cost is also the result of allocations decisions taken by the manager to satisfy the fund performance and risk objectives.

## KEYWORDS

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trend following, hedge funds, portfolio construction, liquidity