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Three Essays in Asset Pricing and Climate Finance

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Contents

List of Tables

List of Figures

Résumé

Cette thèse, divisée en trois chapitres, contribue à la vaste et récente littérature sur l'évaluation des actifs et la finance climatique. Le premier chapitre contribue à la littérature sur la finance climatique tandis que les deux derniers contribuent à la littérature sur l'évalutaion des actifs.

Le premier chapitre analyse comment les politiques environnementales visant à réduire les émissions de carbone affectent les prix des actifs et la consommation des ménages. En utilisant de nouvelles données, je propose une mesure des émissions de carbone du point de vue du consommateur et une mesure du risque de croissance de la consommation de carbone. Les mesures sont basées sur des informations sur la consommation totale et l'empreinte carbone de chaque bien et service. Pour analyser les effets des politiques environnementales, un modèle de risques de long terme est développé dans lequel la croissance de la consommation comprend deux composantes: le taux de croissance de la consommation de carbone et le taux de croissance de la part de la consommation de carbone dans la consommation totale. Ce chapitre soutient que le risque de long terme de la croissance de la consommation provient principalement de la croissance de la consommation de carbone découlant des politiques et des actions visant à réduire les émissions, telles que l'Accord de Paris et la Conférence des Nations Unies sur le changement climatique (COP26). Mon modèle aide à détecter le risque de long terme dans la consommation des politiques climatiques tout en résolvant simultanément les énigmes de la prime de risque et de la volatilité, et en expliquant la coupe transversale des actifs. La décomposition de la consommation pourrait conduire à identifier les postes de consommation les plus polluants et à construire une stratégie d'investissement minimisant ou maximisant un critère environnemental de long terme.

Le deuxième chapitre (*co-écrit avec René Garcia et Caio Almeida*) étudie le rôle des facteurs non linéaires indépendants dans la valorisation des actifs. Alors que la majorité des facteurs d'actualisation stochastique (SDF) les plus utilisés qui expliquent la coupe transversale des rendements boursiers sont obtenus à partir des composantes principales linéaires, nous montrons dans ce deuxième chapitre que le fait de permettre la substitution de certaines composantes principales linéaires par des facteurs non linéaires indépendants améliore systématiquement la capacité des facteurs d'actualisation stochastique de valoriser la coupe transversale des actifs. Nous utilisons les 25 portefeuilles de Fama-French, cinquante portefeuilles d'anomalies et cinquante anomalies plus les termes d'interaction basés sur les caractéristiques pour tester l'efficacité des facteurs dynamiques non linéaires. Le SDF estimé à l'aide d'un mélange de facteurs non linéaires et linéaires surpasse ceux qui utilisent uniquement des facteurs linéaires ou des rendements caractéristiques bruts en termes de performance mesurée par le R^2 hors échantillon. De plus, le modèle hybride - utilisant à la fois des composantes principales non linéaires et linéaires - nécessite moins de facteurs de risque pour atteindre les performances hors échantillon les plus élevées par rapport à un modèle utilisant uniquement des facteurs linéaires.

Le dernier chapitre étudie la prévisibilité du rendement des anomalies à travers les déciles à l'aide d'un ensemble de quarante-huit variables d'anomalie construites à partir des caractéristiques de titres individuels. Après avoir construit les portefeuilles déciles, cet article étudie leur prévisibilité en utilisant leurs propres informations passées et d'autres prédicteurs bien connus. Les analyses révèlent que les rendements des portefeuilles déciles sont persistants et prévisibles par le ratio de la valeur comptable sur la valeur de marché de l'entreprise, la variance des actions, le rendement des dividendes, le ratio des prix sur les dividendes, le taux de rendement à long terme, le rendement des obligations d'entreprise, le TED Spread et l'indice VIX. De plus, une stratégie consistant à prendre une position longue sur le décile avec le rendement attendu le plus élevé et à prendre une position courte sur le décile avec le rendement attendu le plus bas chaque mois donne des rendements moyens et un rendement par risque bien meilleurs que la stratégie traditionnelle fondée sur les déciles extrêmes pour quarante-cinq des quarante-huit anomalies.

Mots-clés: Émissions de carbone, Risque carbone, Risque de long terme, Valorisation des actifs, Composantes principales non linéaires, Coupe transversale des rendements, Facteurs d'actualisation stochastiques, Entropie, Réduction de dimension, Rendements des portefeuilles déciles, Prévisibilité, Limite à l'arbitrage, Stratégie d'investissement.

Abstract

This thesis, divided into three chapters, contributes to the vast and recent literature on asset pricing, and climate finance. The first chapter contributes to the climate finance literature while the last two contribute to the asset pricing literature.

The first chapter analyzes how environmental policies that aim to reduce carbon emissions affect asset prices and household consumption. Using novel data, I propose a measure of carbon emissions from a consumer point of view and a carbon consumption growth risk measure. The measures are based on information on aggregate consumption and the carbon footprint for each good and service. To analyze the effects of environmental policies, a long-run risks model is developed where consumption growth is decomposed into two components: the growth rate of carbon consumption and the growth rate of the share of carbon consumption out of total consumption. This paper argues that the long-run risk in consumption growth comes mainly from the carbon consumption growth arising from policies and actions to curb emissions, such as the Paris Agreement and the U.N. Climate Change Conference (COP26). My model helps to detect long-run risk in consumption from climate policies while simultaneously solving the equity premium and volatility puzzles, and explaining the cross-section of assets. The decomposition of consumption could lead to identifying the most polluting consumption items and to constructing an investment strategy that minimizes or maximizes a long-term environmental criterion.

The second chapter ((*co-authored with René Garcia, and Caio Almeida*)) studies the role of truly independent nonlinear factors in asset pricing. While the most successful stochastic discount factor (SDF) models that price well the cross-section of stock returns are obtained from regularized linear principal components of characteristic-based returns we show that allowing for substitution of some linear principal components by independent nonlinear factors consistently improves the SDF's ability to price this cross-section. We use the Fama-French 25 ME/BM-sorted portfolios, fifty anomaly portfolios, and fifty anomalies plus characteristic-based interaction terms to test the effectiveness of the nonlinear dynamic factors. The SDF estimated using a mixture of nonlinear and linear factors outperforms the ones using solely linear factors or raw characteristic returns in terms of out-of-sample R^2 pricing performance. Moreover, the hybrid model –using both nonlinear and linear principal components– requires fewer risk factors to achieve the highest out-of-sample performance compared to a model using only linear factors.

The last chapter studies anomaly return predictability across deciles using a set of forty-eight anomaly variables built using individual stock characteristics. After constructing the decile portfolios, this paper studies their predictability using their own past information, and other well-known predictors. The analyses reveal that decile portfolio returns are persistent and predictable by book-to-market, stock variance, dividend yield, dividend price ratio, long-term rate of return, corporate bond return, TED Spread, and VIX index. Moreover, a strategy consisting of going long on the decile with the highest expected return and going short on the decile with the lowest expected return each month gives better mean returns and Sharpe ratios than the traditional strategy based on extreme deciles for forty-five out of forty-eight anomalies.

Keywords: Carbon emissions, Carbon risk, Long-run risk, Asset pricing, Nonlinear principal components, Cross-section of returns, Stochastic discount factors, Entropy, Dimension reduction, Decile portfolio returns, Predictability, Limit to arbitrage, Trading strategy.

Chapter 1

Long-Run Carbon Consumption Risks Model and Asset Prices

1.1 Introduction

Regulators are increasingly worried about the extent to which stock markets efficiently price climate change risks and the discount rate that should be used to evaluate investments' uncertain future benefits. In fact, part of these risks stems from the transition to a low-carbon economy. More precisely, to curb carbon dioxide (CO2) emissions, climate policy aims to hold the increase in the average global temperature to within $2°C$ of pre-industrial levels. A burgeoning climate finance literature examines the efficiency of capital markets in pricing risks associated with climate change. For a detailed recent literature review, see Hong et al. (2020) and Giglio et al. (2020).

This market price related to carbon emissions, however, is narrowly confined to the production level and neglects carbon leakage inside and outside a given boundary[0]. Carbon leakage alludes to the situation that may take place if, for any cost-related reasons for climate actions, firms were to transfer production to other countries with fewer pollution-related constraints. This delocalization of production activities could lead to an increase in the total emissions of the corresponding firm. Thus, the production-based market price of carbon emissions incorrectly measures the actual impact of the carbon emissions. Moreover, as depicted in Figure 1.1, since 1998, carbon emissions in the United States, as measured with the consumption-based approach, are consistently larger than those measured with the production-based approach. Hence, the use of production-based emissions minimizes the real CO2 emissions in the atmosphere. Despite this fact, most papers and climate policies focus on the production side. This paper addresses this issue by providing a consumption-based carbon emissions measure using 12 consumption categories. Using the consumption-based carbon emissions approach has two benefits.

[0]Production-based carbon emissions exclusively refer to emissions generated at the point of production—that is, emissions physically produced

First, it captures carbon leakage. Second, it captures the life cycle of greenhouse gases (GHG) emissions expressed in a CO2 equivalent. The life cycle assessment gives a more complete picture of a product's environmental impact. It tells us about the parts of its life cycle period during which the product most negatively affects the environment.

Climate change is a long-horizon phenomenon. But our actions today can help mitigate and adapt to that forthcoming risk. Our mitigation and adaptation actions will be efficient if we have a deep understanding of that long-run risk. To better understand the climate change effects on the economy, we need a long-run risks model. However, the canonical long-run risks (LRR) model studied by Bansal and Yaron (2004) is not suitable for analyzing climate risk, nor is it suitable for analyzing the effects of environmental policies on asset prices and household consumption. The reasons are twofold. First, the dynamics of the consumption growth rate in the canonical LRR model are not directly affected by any climate-related variable. Second, it is difficult to detect long-run risk in consumption coming from the canonical model (Bansal et al. (2007a), Bansal et al. (2007b), Pohl et al. (2018), Schorfheide et al. (2018) among others). Therefore, we need a new long-run risks model that specifies the consumption growth rate dynamics such that long-run risk is easily detectable and consumption growth is directly affected by climate-related shocks. This paper proposes such a model based on insight from Bansal et al. (2016b), Bansal et al. (2017), and Giglio et al. (2021b).

This paper adds two contributions to the existing literature. First, I use novel data to provide a consumption-based carbon emissions measure. Second, I introduce a long-run carbon consumption risks model that departs from the existing long-run risks model through its decomposition of consumption growth into two components: carbon consumption growth and growth in the share of carbon consumption. The first component captures the effect of carbon consumption on aggregate consumption, and the second component captures the effect of green consumption. In addition, my model differs from the current literature in its ability to study the effects of environmental policies on asset prices and household consumption.

To that end, this paper links the carbon footprint information of each good and service from the Economic Input-Output Life Cycle Assessment (EIO-LCA) database and the aggregate consumption information of the same goods and services from the national income and product accounts (NIPA) consumption data to construct my consumption-based carbon dioxide emissions measure. To the best of my knowledge, this paper is the first to link the NIPA and EIO-LCA data to provide a consumption-based carbon emissions measure. Then, I use industry-level returns data from Kenneth R. French's website to empirically test the long-run carbon consumption risks model.

To assess the impact of climate change on macro-financial variables such as dividend growth, the equity premium, and consumption growth, this paper decomposes the consumption growth rate into two components: the carbon consumption growth component and the share of the carbon consumption growth component. In our setting, "carbon consumption risk" occurs for two main reasons. First, carbon risk stems from regulators' willingness to curb carbon emissions at the pre-industrial level, which in turn may affect future household consumption that heavily depends on carbon consumption. Second, carbon consumption creates damage through the lens of climate change. As a result, carbon-based consumption carries potential long-run risks in both cases. Building on this insight, I theoretically characterize and then quantify carbon price risk in an asset pricing model with long-run risks in carbon consumption. This paper argues that the long-run risk in consumption growth comes mainly from the carbon consumption growth arising from policies and actions to curb emissions, such as the Paris Agreement and the U.N. Climate Change Conference (COP26). I hypothesize that the growth rate of the share of carbon consumption out of total consumption does not carry any long-run risks.

Turning to the findings, we see that the decomposition of consumption growth gives more flexibility to policymakers in their efforts to stimulate consumption. They can target either carbon consumption or the share of carbon consumption out of total consumption. For example, one standard deviation negative shock to the expected carbon consumption –such shock could be a policy aiming to reduce the long-run carbon consumption– causes consumption growth to decrease by 5.5% for sixty months using the full sample parameter estimates. It decreases dividend growth, market return, and the risk free rate by 8%, 3.7%, and 4% respectively. Further analysis over different sub-periods shows that the impacts of environmental policies on asset prices and household consumption are bigger during periods of high climate change uncertainty. In fact, the decrease in consumption growth is approximately 2%, 3%, and 11% during the periods 1930–1955, 1956–1980, and 1981–2018, respectively. The effects of the policy disappear after sixty periods – corresponding to five years. A direct shock on carbon consumption growth –such as policies aiming to reduce the short-run carbon consumption–, leads to a mitigated and ambiguous effect on consumption.

In addition, my model helps to detect future persistent fluctuations in the mean and volatility of carbon consumption growth arising from environmental policies. It also doubles the ability to detect long-run risks, as compared to the canonical model, while also solving the equity premium and volatility puzzles. My model is especially useful during periods of high climate change uncertainty, such as the period after the election of President Ronald Reagan in the US.

This article is related to the strand of literature on the long-run risks model. Papers here include Bansal and Yaron (2004), Bansal et al. (2007a), Bansal et al. (2007b), Koijen et al. (2010), Bonomo et al. (2011), Constantinides and Ghosh (2011), Schorfheide et al. (2018), Pohl et al. (2018), and Pohl et al. (2021). These papers model consumption growth dynamics as containing a small, predictable component. In these papers, long-run risks come from the aggregate consumption growth rate, and the economy is governed by two state variables: expected consumption growth and the conditional volatility of consumption growth. They find that expected consumption growth is highly persistent and that long-run risks are difficult to detect. To depart from this literature, I consider new consumption growth dynamics that allow me to study the effects of environmental policies on asset prices and household consumption beyond the usual effects analyzed by the canonical LRR model. I decompose the consumption growth rate into two parts: a carbon growth component, which creates long-run growth risk, and a share of the carbon growth component, which does not create any long-run risk but does affect the dynamics of consumption growth and acts as a hedge against carbon risk. In the previously cited papers, long-run risk comes directly from aggregate consumption growth, which is barely detectable. This decomposition allows me to study the effects of climate change on macro-financial variables such as consumption growth, dividend growth, and the equity premium.

My study is also related to the strand of literature on climate finance. Papers here include Daniel et al. (2016), Bansal et al. (2016b), Bansal et al. (2017), Chen et al. (2019), Giglio et al. (2021b), and Stroebel and Wurgler (2021), Avramov et al. (2022). This paper focuses on carbon or transition risk,[1] whereas the previously cited papers study the physical risk side of climate risk[2]. In particular, since climate change is a long-horizon phenomenon, we need to assess it using a long-run risks model by looking at the consumption or household side.

The rest of the paper is organized as followed. Section 1.2 describes the methodology used to build a new measure of consumption-based carbon risk. Section 1.3 sets up the theoretical model. Section 1.4 presents the results and the asset pricing implications of the model, and section 1.5 concludes.

[1]Carbon or transition risk is that which is inherent to the process of transitioning to a lower-carbon economy. Examples include policy and legal risks, technology risk, market risk, and reputation risk.

[2]Physical risk includes event-driven risks that damage assets and disrupt the supply chain (examples include hurricanes, floods, and fires), and long-term shifts in climate patterns (for example, increasing temperatures or rising sea levels).

1.2 A measure of consumption-based carbon risk

The central challenge of climate finance is to capture the actual impact of carbon emissions. To address that challenge, this paper uses aggregate consumption data and the carbon footprint to identify a carbon/green risk measure. All data are on an annual basis and span the period 1930–2018. I describe below how I constructed the carbon consumption, green consumption measures to assess the empirical implications of a long-run carbon consumption risks model. Summary statistics are presented in table 1.1.

To construct the carbon consumption measure, I consider carbon dioxide emissions from a household consumption perspective. These carbon dioxide emissions indicators provide an alternative view of carbon dioxide emissions, where the emissions are tied to the consumption of durable goods, non-durable goods, and services in the United States. This approach allows for accounting for a potential carbon leakage and the actual impact of carbon emissions within a given boundary. In fact, under the assumption of a linear life cycle progression of a product, households stand at the usage stage where they have control of the product. Using NIPA data, I collect aggregate information on 12 consumption categories (food, clothing, housing, furniture, health, transportation, communication, recreation, education, food services and accommodation, financial services and insurance, and other goods and services.)[3]. Then, I match this aggregate information to the carbon footprint information provided by the Economic Input-Output Life Cycle Assessment (EIO-LCA) database using the purchaser (retail) price model[4]. The Life Cycle Assessment (LCA) investigates, estimates, and evaluates the environmental burdens imposed by a material, product, process, or service throughout its life span. Environmental burdens include the materials and energy resources required to create the product, as well as the wastes and emissions generated during the process. The EIO-LCA is developed by Carnegie Mellon University (Institute. (2021)) and provides an estimate of economy-wide cradle-to-gate GHG emissions per dollar of producer output for 428 sectors of the US economy. This paper uses the US 2002 benchmark model - purchaser price[5] to collect the carbon footprint for the 11 household expenditure categories identified in the NIPA data. I identify in the EIO-LCA database a total of 50 sectors representing household consumption good production. A sample of such carbon emissions is given in figure 1.2 for power generation and supply (electricity), and soft drinks and ice manufacturing. It depicts the direct and indirect emissions related to the purchase of $US 1 million of electricity (top panel) and soft drinks (bottom panel). It amounts to 9,370 and 651 tons of CO2 emissions (t CO2e), respectively. Note that electricity places a higher

[3]NIPA is an abbreviation for the national income and product accounts from the Bureau of Economic Analysis. I use annual aggregate consumption data for US households from the period 1930 to 2018.

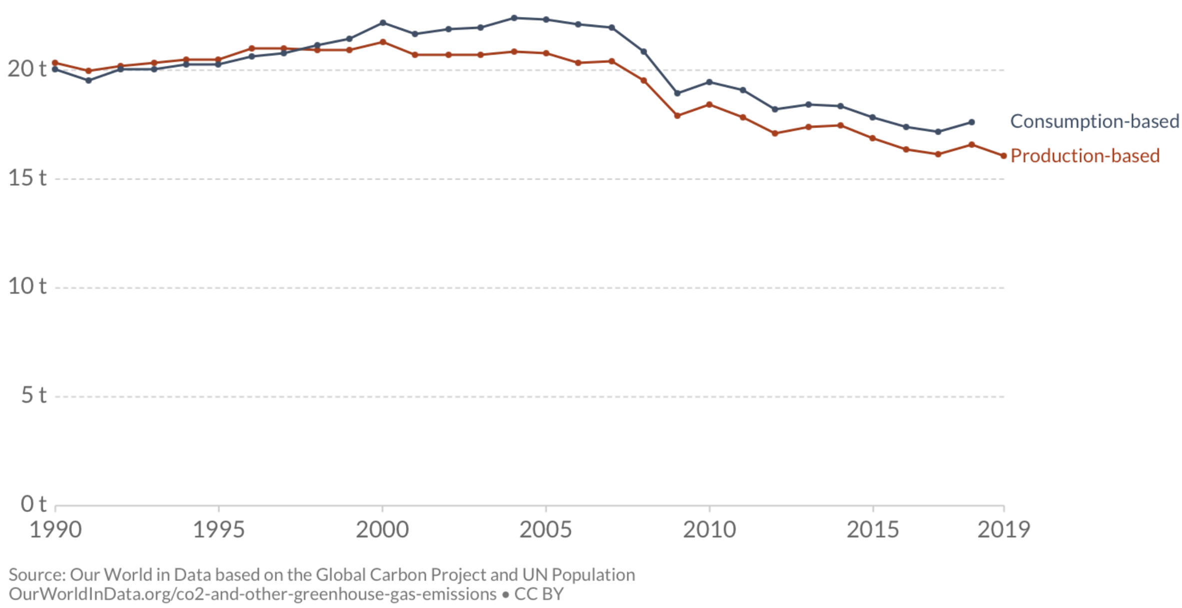
[4]The purchaser (retail) price model is a commodity-based model. The purchaser model is designed to adjust for retail to producer prices and thus models the delivery and retailing stages of the supply chain. It also allows for the modeling of commodities as opposed to industrial activity (e.g., a car instead of "automobile production").

[5]The US 2002 model uses information on the 2002 US economy.

burden on the environment than soft drinks.

Using these 50 sectors, I covered 96% of total household consumption expenditure, which represents a total of 29 consumption goods out of 44 in the NIPA data table. In figure 1.3, the x-axis captures the tons of CO2 emissions (tCO2e) per million US dollars. Figure 1.3 displays the total carbon footprint in each consumption category. As shown, transportation, food, and housing account for a large part of the carbon footprint in household consumption expenditure, representing a total of 77% of US household CO2 emissions. In household consumption baskets, food and beverages contribute the most to the carbon footprint, followed by housing, household utilities, furnishings, recreation, and transportation.

Figure 1.1: Fact



The direct carbon dioxide emissions, which include natural gas, motor oil, and lubricant oil, represent only 11% of the total emissions in the household consumption basket. In this paper, we use both direct and indirect burdens to compute the total carbon emissions.

Next, I map the NIPA expenditure category to the carbon footprint information to compute the consumption-based carbon measure. Since the carbon footprint information is related to the 2002 consumer price purchase, all of the NIPA data are deflated using the 2002 reference base period for the consumer price index (CPI). Figure 1.2 shows that all of the consumption categories do not affect the environment equally. Therefore, this paper weights the aggregate consumption of each good and service by its burden on the atmosphere to compute a new total consumption measure. The total US household

Figure 1.2: Carbon footprint of electricity versus soft drinks

	Sector	Total t CO2e	CO2 Fossil t CO2e	CO2 Process t CO2e	CH4 t CO2e	N2O t CO2e	HFC/PFCs t CO2e
	Total for all sectors	*9370*	*8880*	*31.3*	*346.*	*56.3*	*57.5*
221100	Power generation and supply	8820	8690	0.000	23.9	54.0	55.9
212100	Coal mining	230	25.9	0.000	204.0	0.000	0.000
211000	Oil and gas extraction	129.0	36.3	23.6	69.0	0.000	0.000
486000	Pipeline transportation	67.1	30.7	0.084	36.3	0.000	0.000
482000	Rail transportation	25.9	25.9	0.000	0.000	0.000	0.000
324110	Petroleum refineries	19.8	19.8	0.000	0.061	0.000	0.000
484000	Truck transportation	9.17	9.17	0.000	0.000	0.000	0.000

(a) Power generation and supply

Sector #312110: Soft drink and ice manufacturing
Economic Activity: $1 Million Dollars
Displaying: Greenhouse Gases
Number of Sectors: Top 10

Change Inputs (Click here to view greenhouse gases, air pollutants, etc...)

Documentation:
The sectors of the economy used in this model.
The environmental, energy, and other data used and their sources.

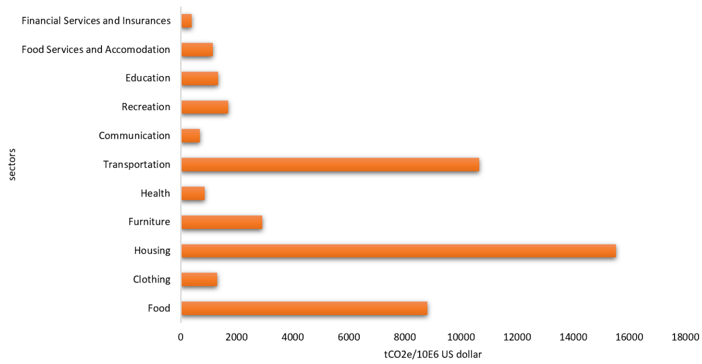
Frequently asked questions about IO-LCA (or EEIO) models.

This EIO-LCA data model was contributed by Green Design Institute.

	Sector	Total t CO2e	CO2 Fossil t CO2e	CO2 Process t CO2e	CH4 t CO2e	N2O t CO2e	HFC/PFCs t CO2e
	Total for all sectors	*651.*	*513.*	*30.6*	*50.9*	*37.3*	*19.4*
221100	Power generation and supply	234.0	230	0.000	0.633	1.43	1.48
311221	Wet corn milling	33.1	33.1	0.000	0.000	0.000	0.000
33131A	Alumina refining and primary aluminum production	31.7	7.18	11.2	0.000	0.000	13.2
484000	Truck transportation	30.7	30.7	0.000	0.000	0.000	0.000
1111B0	Grain farming	26.6	3.92	0.000	2.17	20.5	0.000
211000	Oil and gas extraction	26.4	7.44	4.84	14.1	0.000	0.000
312110	Soft drink and ice manufacturing	20.4	20.4	0.000	0.000	0.000	0.000
325190	Other basic organic chemical manufacturing	20.0	18.0	0.000	0.000	2.06	0.000
324110	Petroleum refineries	15.0	15.0	0.000	0.047	0.000	0.000
33131B	Aluminum product manufacturing from purchased aluminum	14.6	14.6	0.000	0.000	0.000	0.000

(b) Soft drinks and ice manufacturing

Figure 1.3: Carbon footprint by household expenditure category.



Note: The x-axis captures the tons of CO2 emissions (tCO2e) per million US dollars

consumption-based carbon emissions can be expressed simply as the product of consumption, denoted C, in dollars, and carbon emissions per unit of consumption, denoted CE, summed over each carbon footprint activity (i) included in the model. Put simply, when it comes to analyzing the effect of carbon emissions on the economy and environment, consumption categories should not be treated the same. Each category affects the environment differently , so I compute the aggregate consumption by weighting each category consumption by its footprint. Alternatively, I classify the carbon footprint in decreasing order and use the five categories with the highest carbon footprints to compute what I call "carbon consumption" and whatever is left over to compute "green consumption." Overall, the total carbon emissions at any time t are calculated as follows:

$$TC_t = \sum_{i=1}^{11} C_{i,t} * CE_i \tag{1.1}$$

However, I subdivide all of the consumption categories into two parts in order to separate the usual consumption risk into two risks. The first risk measures the carbon consumption risk—including the consumption categories that pollute the most based on their carbon footprint; see equation 1.2). The second risk measures the green consumption risk—including the consumption categories that pollute the least based on their carbon footprint; see equation 1.3). Henceforth, I will call the risk associated with green consumption "green risk" and the risk associated with carbon consumption "carbon risk".

$$\boldsymbol{CC_t = \sum_{i=1}^{5} C_{i,t} * CF_i \quad or \quad \sum_{i=1}^{5} C_{i,t}} \tag{1.2}$$

$$\boldsymbol{GC_t = \sum_{i=6}^{11} C_{i,t} * CF_i \quad or \quad \sum_{i=6}^{11} C_{i,t}} \tag{1.3}$$

The pattern of those components is shown in figure 1.4 in terms of log difference:

$$\Delta cc_{t+1} = log\left(\frac{CC_{t+1}}{CC_t}\right) \tag{1.4}$$

$$\Delta gc_{t+1} = log\left(\frac{GC_{t+1}}{GC_t}\right) \tag{1.5}$$

$$\Delta \alpha_{cc,t+1} = log\left(\frac{\alpha_{cc,t+1}}{\alpha_{cc,t}}\right), \tag{1.6}$$

where $\alpha_{cc,t} = \frac{CC_t}{C_t}$. I call Δcc_{t+1} carbon consumption growth risk, Δgc_{t+1} green consumption growth risk, and $\Delta \alpha_{cc,t}$ the share of carbon consumption growth risk. I could have defined the share of green consumption growth risk ($\Delta \alpha_{gc,t}$) in the same manner.

Figure 1.4 displays the time series of the key variables of this paper. One can clearly see that the series replicate some business cycles and climate change events. Specifically, when consumption growth goes up, carbon consumption growth goes up too which corroborates the fact that a significant part of the household's baskets is carbon. In addition, the peaks and troughs of these two series[6] occur at the same time. Green consumption follows a similar pattern with some lags and some periods where it decreases while carbon consumption or total consumption is going up[7]

To link the real economy to the financial market, I also use data on industry, small, large, value, and growth portfolio returns from Kenneth R. French's website. I use value-weighted portfolios including and excluding dividends to compute the dividend and price series on a per-share basis (Campbell and Shiller (1988), Hansen et al. (2008)). Table 1.1 presents some descriptive statistics. All returns and dividend growth series have been deflated using CPI growth.

1.3 Model

The model builds on the Bansal and Yaron (2004) LRR model and uses insight from Giglio et al. (2021b). My model introduces three state variables: a long-run risk variable, the variance of the innovation of carbon consumption growth alongside the growth rate of the share of carbon consumption out of total consumption that jointly drive the conditional mean of carbon consumption growth, and dividend growth.

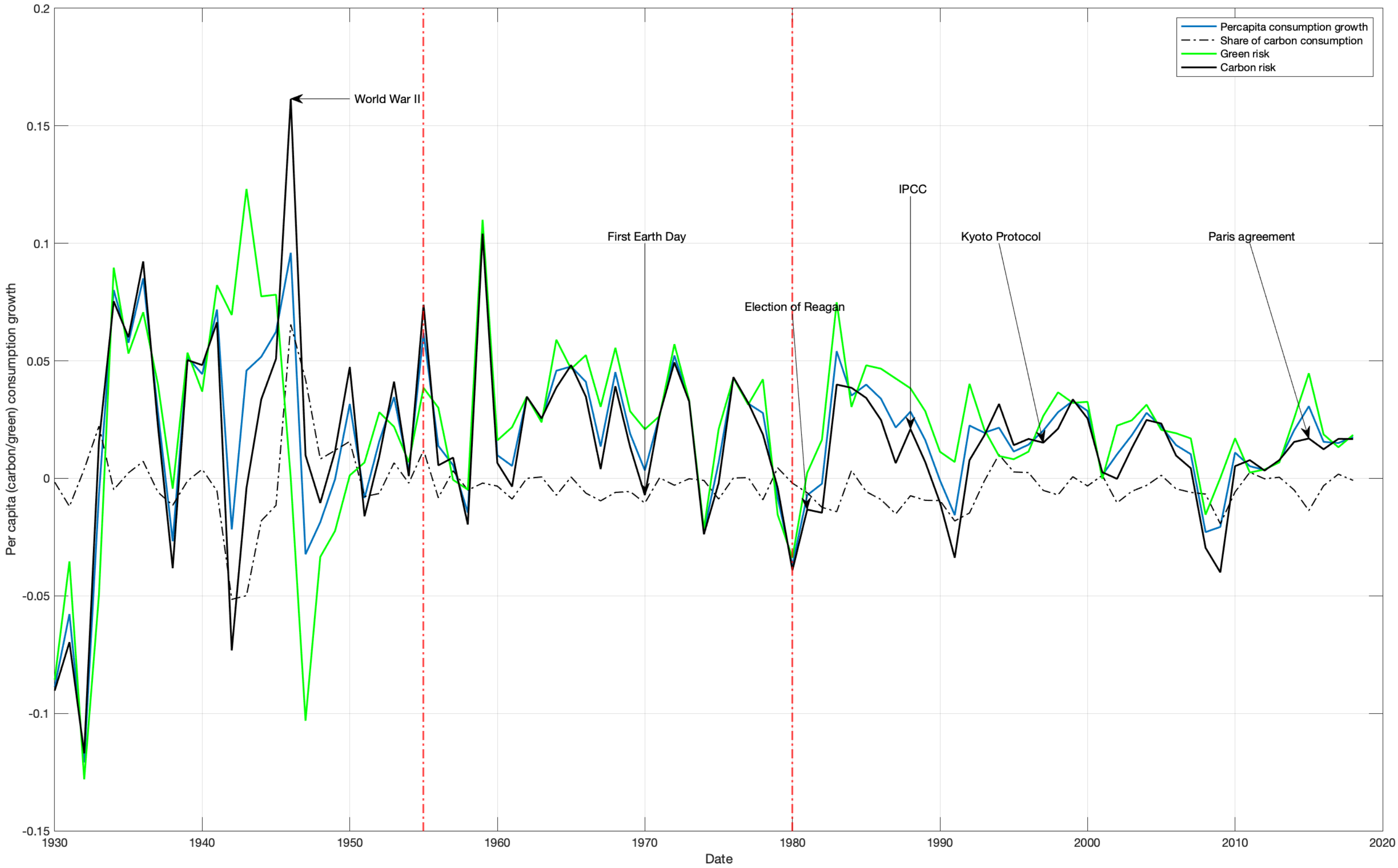
1.3.1 Preferences

In this economy, there is a representative household with recursive preferences (Kreps and Porteus (1978), Epstein and Zin (1989)). This paper chooses these types of preferences for

[6]Consumption and carbon consumption growths

[7]During the World War II period for example.

Figure 1.4: Carbon risk, green risk, and household expenditure growth



two main reasons: First, they allow for separation between the coefficient of risk aversion and the elasticity of intertemporal substitution. Second, an Epstein–Zin (EZ) investor's marginal utility depends on both the one-period innovation in the consumption growth rate and news about consumption growth at future horizons. This feature is important for the climate change thematic as news about future global warming will affect consumers' consumption behaviors. Hence, consumption growth will incur a proportional shock. One would like a utility function specification that affects the level of the climate risk premium and the term structure of the discount rate. Epstein-Zin utility specified in equation 1.7 does what I just described:

$$V_t = \left[(1-\delta) C_t^{\frac{1-\gamma}{\theta}} + \delta \left(E_t [V_{t+1}]^{1-\gamma} \right)^{\frac{1}{\theta}} \right]^{\frac{\theta}{1-\gamma}} \tag{1.7}$$

Table 1.1: Summary statistics

	$E(.)$	$\sigma(.)$	AC(1)	AC(2)	AC(3)	AC(4)	AC(5)
				Macro variables			
Δc	0.0178	0.0343	0.3150	0.0608	-0.1508	-0.1491	0.0098
$\Delta\alpha_{cc}$	-0.0030	0.0134	0.4545	0.0574	-0.1233	-0.2765	-0.1730
Δcc	0.0147	0.0382	0.2717	-0.0223	-0.2057	-0.1549	0.0176
$\Delta\alpha_{gc}$	0.0042	0.0215	0.4469	0.0640	-0.0749	-0.2692	-0.2105
Δgc	0.0220	0.0385	0.4647	0.2063	-0.0167	-0.2016	-0.1006
				Financial variables			
Δd	0.0176	0.1223	0.1075	-0.1832	-0.1502	-0.0930	0.0459
z_m	3.3878	0.5123	0.9276	0.8524	0.7992	0.7605	0.7163
r_m	0.0694	0.1929	0.0077	-0.2202	0.0181	-0.0053	-0.1215
r_f	0.0025	0.0351	0.6852	0.3059	0.2040	0.2336	0.2788

The table reports the sample mean, standard deviation, and first-order to fifth-order autocorrelation of the marketwide log price-dividend ratio, the log dividend, consumption, and the (share of) carbon/green consumption growth rates.

where δ is the subjective discount factor parameter, $\gamma > 0$ is the coefficient of risk aversion, and $\theta = \frac{1-\gamma}{1-\frac{1}{\psi}}$ with $\psi > 0$ represents the elasticity of intertemporal substitution (EIS). The standard time-separable power utility model is a special case of the EZ utility when $\gamma = \frac{1}{\psi}$. The agent prefers early resolution of the risk if $\gamma > \frac{1}{\psi}$ and late resolution if $\gamma < \frac{1}{\psi}$.

In this formulation, the household evaluates her consumption plan recursively. She consumes at time t and receives a continuation value of her consumption, which can bear a long-run risk component through its carbon consumption. Indeed, with a canonical expected utility risk, only short-run risks are compensated, whereas long-run risks do not carry a separate risk premium. With the above preference, long-run risks earn a positive risk premium if households prefer an early resolution of uncertainty.

Furthermore, there are $N+1$ tradable assets in the economy: one risk-free asset ($i = 0$) and N risky assets ($i = 1, \ldots, N$). In each period t, the representative household invests X_{it} unit of its discretionary wealth in asset i. The tradable asset i has a price of P_{it} and a future dividend of D_{it}, with a gross return of $R_{it+1} = \frac{D_{it+1}+P_{it+1}}{P_{it}}$. The intertemporal budget constraint faced by the household is given by

$$C_t + \sum_{i=1}^{N+1} P_{it}X_{i,t+1} = \sum_{i=1}^{N+1} (P_{it} + D_{it})X_{it} = W_t \tag{1.8}$$

where

$$C_t = CC_t + GC_t$$

is total consumption and the sum of the consumption considered as carbon consumption (CC_t) and the consumption considered as green consumption (GC_t).

1.3.2 A long-run carbon consumption risks (LRCCR) model

This paper assumes that consumption growth in the economy depends on two components. One carries a long-run risk, and the other does not carry any long-run risks. In particular, we assume that aggregate consumption growth is given by (the proof can be found in appendix A.1):

$$\Delta c_{t+1} = \underbrace{\Delta cc_{t+1}}_{Carbon} - \underbrace{\Delta\alpha_{cc,t+1}}_{share\ of\ cc}, \tag{1.9}$$

where $\Delta c_{t+1} = log\left(\frac{C_{t+1}}{C_t}\right)$ is the log consumption growth rate. The expression Δcc_{t+1} is the growth rate of carbon consumption and $\Delta\alpha_{cc,t+1}$ is the growth rate of the share of carbon consumption in total consumption as defined in section 1.2, equations 1.4–1.6. Note that the conditional mean of Δcc_{t+1} and its conditional volatility are a potential source of carbon consumption risk. In fact, the transition to a low-carbon economy raises the future likelihood of carbon consumption risk, which, if realized, leads to a consumption risk. For instance, the nationally determined contributions (NDC) policy scenario aims to reduce carbon consumption by 32(15) gigatons of CO2 to stay within the 1.5°C(2°C) limit by 2030. The dynamics of the other variables are described as follows:

$$\Delta cc_{t+1} = \nu_{cc} + x_t + \sigma_t\epsilon_{cc,t+1} \tag{1.10}$$

$$x_{t+1} = \rho_x x_t + \psi_x\sigma_t\epsilon_{x,t+1} \tag{1.11}$$

$$\sigma^2_{t+1} = (1-\nu)\sigma^2 + \nu\sigma^2_t + \sigma_w\epsilon_{\sigma,t+1} \tag{1.12}$$

Thus, in our model x_t, $\Delta\alpha_{cc,t}$, and σ^2_t are the state variables. In particular, x_t captures the conditional mean of the carbon consumption growth rate, while σ^2_t captures the uncertainty associated with the transition to a lower-carbon economy. The growth of the share of carbon consumption out of total consumption component doesn't carry any long-run risk and evolves, as given by

$$\Delta\alpha_{cc,t+1} = \nu_\alpha(1-\rho_\alpha) + \rho_\alpha\Delta\alpha_{cc,t} + \sigma_\alpha\epsilon_{\alpha,t+1} + \pi\sigma_t\epsilon_{cc,t+1} \tag{1.13}$$

This paper assumes that innovations in the share of carbon consumption out of total consumption and carbon consumption are correlated. That correlation depends on the parameters π[8] and σ_α. Finally, the dividend growth rate of any dividend-paying asset i

[8] Alternative specification : $\epsilon_{\alpha,t}$ and $\epsilon_{cc,t}$ are correlated instead of i.i.d. and set $\pi = 0$

is as follows:

$$\Delta d_{i,t+1} = \nu_i + \phi_i x_t + \phi_{\alpha,i}\Delta\alpha_{cc,t} + \psi_i \sigma_t \epsilon_{i,t+1} \tag{1.14}$$

where ϕ_i, $\phi_{\alpha,i}$, ψ_i determine asset i's exposure to the long-run share of carbon consumption and volatility risks, respectively. The shocks $\epsilon_{x,t+1}$, $\epsilon_{\alpha,t+1}$, $\epsilon_{i,t+1}$, $\epsilon_{cc,t+1}$, and $\epsilon_{\sigma,t+1}$ are assumed to be i.i.d. N(0,1) and mutually independent if $\pi \neq 0$. Equations (1.9)–(1.14) represent the building blocks of our long-run carbon consumption risks model, henceforth LRCCR model. The dynamics of the variables and the utility function involve 17 parameters Θ=[ρ_x ψ_x ψ_i ν_{cc} ν ν_i σ_w σ ϕ_i δ γ ψ ν_α ρ_α σ_α π $\phi_{\alpha,i}$]. I calibrate the model parameters to match key sample moments. I derive some moments conditions for carbon consumption, the share of carbon consumption, and asset i dividend growth rates as functions of the time series and the preferences parameters. See the appendices A.3 for more details.

1.3.3 Solving the model

For any asset i, the corresponding Euler equation regarding the consumer's utility maximization is given by

$$\mathbb{E}_t[e^{m_{t+1}+r_{i,t+1}}] = 1 \tag{1.15}$$

where

$$m_{t+1} = \theta log(\delta) - \frac{\theta}{\psi}\Delta cc_{t+1} + \frac{\theta}{\psi}\Delta\alpha_{cc,t+1} + (\theta - 1)r_{c,t+1} \tag{1.16}$$

is the natural logarithm of the stochastic discount factor; $\mathbb{E}_t[.]$ denotes expectation conditional on time t information; $r_{i,t+1}$ is the continuously compounded return on asset i; and $r_{c,t+1}$ is the unobservable continuously compounded return on an asset that delivers aggregate consumption as its dividend each period.

Following Campbell and Shiller (1988), the log return on the consumption claim, namely $r_{c,t+1}$, and the log return of the asset i $r_{i,t+1}$ are approximated as follows:

$$r_{c,t+1} = \kappa_0 + \kappa_1 z_{t+1} - z_t + \Delta cc_{t+1} - \Delta\alpha_{cc,t+1} \tag{1.17}$$

$$r_{i,t+1} = \kappa_{0,i} + \kappa_{1,i} z_{i,t+1} - z_{i,t} + \Delta d_{i,t+1} \tag{1.18}$$

where $z_t = \log\left(\frac{P_{m,t}}{C_t}\right)$ and $P_{m,t}$ stands for the market portfolio price, $z_{i,t} = \log\left(\frac{P_{i,t}}{D_{i,t}}\right)$. $\kappa_1 = \frac{e^{\bar{z}}}{1+e^{\bar{z}}}$ and $\kappa_0 = \log\left(1 + e^{\bar{z}}\right) - \kappa_1\bar{z}$ are log-linearization constants. The term $\bar{z}$ denotes the long-run mean of the log price-consumption ratio (z). Regarding equation (1.18),

$\kappa_{1,i} = \frac{e^{\bar{z}_i}}{1+e^{\bar{z}_i}}$ and $\kappa_{0,i} = \log(1 + e^{\bar{z}_i}) - \kappa_1 \bar{z}_i$ where $\bar{z}_i$ denotes the long-run mean of the log price-dividend ratio (z_i). Throughout this paper, subscript m refers to the market portfolio, and subscript i refers to any asset.

As in Bansal and Yaron (2004), I conjecture that z_t and $z_{i,t}$ are affine functions of the state variables x_t (LRR variable or conditional expected carbon consumption growth), σ_t^2 (conditional volatility of the carbon consumption growth), and $\Delta\alpha_{cc,t}$ (share of carbon consumption growth):

$$z_t = A_0 + A_1 x_t + A_2 \sigma_t^2 + A_3 \Delta\alpha_{cc,t} \tag{1.19}$$

$$z_{i,t} = A_{0,i} + A_{1,i} x_t + A_{2,i} \sigma_t^2 + A_{3,i} \Delta\alpha_{cc,t} \tag{1.20}$$

The functions A_0, A_1, A_2, A_3, $A_{0,i}$, $A_{1,i}$, $A_{2,i}$, and $A_{3,i}$ are functions of parameters in Θ and the linearization parameters. Their expressions are given in the appendix A.3. An increase in the expected carbon consumption growth rate will raise the price-consumption ratio if the intertemporal substitution effect dominates the wealth effect. However, a higher share of carbon consumption out of total consumption implies a lower price-consumption ratio when $\psi > 1$. Turning now to the price-dividend ratio, we see that the conclusions are different for the share of the carbon consumption growth effect. While the expected carbon consumption growth measure still raises the price-dividend ratio but is much higher under the conditions that $\psi > 1$ and $\phi_i > 1$ (the LRR variable acts as a leverage), the share of carbon consumption now positively affects the price-dividend ratio, hypothesizing $\phi_{\alpha,i} > 0$.

Using equation 1.15, I show that the log risk-free rate can be written as a function of the state variables as follows:

$$\begin{aligned} r_{f,t} &= -log\mathbb{E}_t[e^{m_{t+1}}] \\ &= A_{0,f} + A_{1,f} x_t + A_{2,f} \sigma_t^2 + A_{3,f} \Delta\alpha_{cc,t} \end{aligned} \tag{1.21}$$

Once again $A_{0,f}$, $A_{1,f}$, $A_{2,f}$, $A_{3,f}$ are functions of parameters in Θ and the linearization parameters, and their expressions are given in the appendix A.3.

1.3.4 Asset pricing implications

To test the implications of the model for the equity premium and the cross section of returns, I combine equations (1.16), (1.17), and (1.19) to get the expression of the stochastic discount factor in terms of state variables:

$$
\begin{aligned}
m_{t+1} = &(\theta log(\delta) + (\theta-1)[\kappa_0 + (\kappa_1 - 1)A_0]) + \left(-\frac{\theta}{\psi} + (\theta - 1)\right)\Delta cc_{t+1} \\
&+ \left(\frac{\theta}{\psi} - (\theta-1) + (\theta-1)\kappa_1 A_3\right)\Delta\alpha_{cc,t+1} \\
&+ (\theta-1)\kappa_1 A_1 x_{t+1} + (\theta-1)\kappa_1 A_2 \sigma^2_{t+1} \\
&- (\theta-1)A_1 x_t - (\theta-1)A_2\sigma^2_t - (\theta-1)A_3\Delta\alpha_{cc,t}
\end{aligned} \tag{1.22}
$$

The innovation in the m_{t+1} conditional on time-t information is given by

$$
m_{t+1} - \mathbb{E}_t[m_{t+1}] = -\lambda_{m,\alpha}\sigma_\alpha\epsilon_{\alpha,t+1} - \lambda_{m,cc}\sigma_t\epsilon_{cc,t+1} - \lambda_{m,x}\sigma_t\epsilon_{x,t+1} - \lambda_{m,w}\sigma_w\epsilon_{\sigma,t+1} \tag{1.23}
$$

Therefore, the equity risk premium for any asset i is

$$
\mathbb{E}_t(r_{i,t+1} - r_{f,t}) + 0.5\mathbb{V}_t(r_{i,t+1}) = \lambda_{m,x}\beta_{i,x}\sigma^2_t + \lambda_{m,w}\beta_{i,w}\sigma^2_w + \lambda_{m,\alpha}\beta_{i,\alpha}\sigma^2_\alpha + \lambda_{m,cc}\beta_{i,cc}\sigma^2_t \tag{1.24}
$$

where the β's are asset i exposure to the long-run risk, the volatility risk, the share of the carbon consumption risk, and the short-run risk, and the λ's are the respective risk prices. The β's and λ's are functions of the preference parameters, the linearization parameters, and the parameters in the dynamics of macro-financial variables (see appendix A.3). The price of the short-run carbon consumption risk and the exposure of any asset to this risk rise with the correlation between the share of carbon growth and the carbon growth. The price of the long-run risk $\lambda_{m,x}$, and the exposure of any asset i to the long-run risk $\beta_{i,x}$ increase with the persistence of the expected carbon consumption growth. In the same way, $\lambda_{m,cc}$, $\lambda_{m,\alpha}$, $\beta_{i,cc}$, and $\beta_{i,\alpha}$ increase with the persistence of the share of carbon consumption out of total consumption growth.

I substitute equation (1.22) into the set of Euler equations (1.15) to have moment conditions that are expressed entirely in terms of observables. Then I examine the empirical plausibility of the model when the set of assets in the economy consists of the market portfolio and the risk-free rate, thereby focusing on the equity premium and risk-free rate puzzles. In particular, I consider a set of moments, namely, the expected value and the standard deviation of the equity premium, the real risk-free rate, and the price-dividend ratio, and I calibrate the parameters Θ to match those moments.

Next, this paper examines whether the model can explain the cross section of returns in different asset classes including "carbon-intensive" (high heat-exposed and low heat-exposed) portfolios and Fama-French 25 portfolios. In total, I use 42 Fama-French industry portfolios, and 25 Fama-French portfolios. I adopt the two-pass regression methodology of Fama and MacBeth (1973) to estimate the risk premia on each risk factor (see also Kan et al. (2013), Bai and Zhou (2015)). I consider the two risks I built, namely, the carbon consumption (cc) growth risk (Δcc_t) and the share of carbon consumption (shcc) growth risk ($\Delta\alpha_{cc,t}$), and Fama and French (1993) three-factors. In the first stage, I compute the portfolio's exposures to the risk factors by regressing each portfolio's excess return ($r_{i,t}$) on Δcc_t, $\Delta\alpha_t$, and on Fama and French (1993) three-factors:

$$r_{i,t} = c_i + \beta_{m,i} mkt_t + \beta_{hml,i} hml_t + \beta_{smb,i} smb_t + \beta_{sh,i} \Delta\alpha_{cc,t} + \beta_{cc,i} \Delta cc_t + \epsilon_{i,t} \quad i = 1, ..., N \quad (1.25)$$

where $r_{i,t}$ is the return of the portfolio i, mkt_t is the market portfolio excess return, smb_t is the size premium (small minus big), hml_t is the value premium (high minus low), the β's are the factor loading's. In the second stage, I run a cross-sectional regression. Put in equation terms, this gives the following:

$$\mu_{r,i} = \gamma_0 + \gamma_m \hat{\beta}_{m,i} + \gamma_{hml} \hat{\beta}_{hml,i} + \gamma_{smb} \hat{\beta}_{smb,i} + \gamma_{sh} \hat{\beta}_{sh,i} + \gamma_{cc} \hat{\beta}_{cc,i} + \epsilon_i \quad i = 1, ..., N \quad (1.26)$$

For comparison purposes, this paper also applies the two-pass regression to the case of Fama and French (1993) three-factors model, and different other specifications. I plot the exposures $\beta_{sh,i}$'s and $\beta_{cc,i}$'s in Figure 1.6 for the model using only my two risk factors. Once we know which portfolio (industry) is significantly positively and negatively exposed to the carbon risk, I calibrate the LRCCR model to match key moments of those portfolios (industries). The main goal is to explain the cross section of the portfolios' (industries') expected returns. My parameters of interest are the leverage parameters—that is, the dividend exposure to the long-run risk variable and to the share of the carbon consumption growth rate for each portfolio (industry) ϕ_i and $\phi_{\alpha,i}$—and the dividend exposure to volatility risks ψ_i. To test the effectiveness of the LRCCR model, I start by looking at the cross-sectional properties of the well-known portfolios, in particular, the value, growth, small size, and large portfolios. Based on empirical evidence (see Bansal et al. (2005) and Hansen et al. (2008), Bansal et al. (2016a)), the value portfolio presents a much higher exposure to low-frequency risks in consumption relative to the growth portfolio. Likewise, the long-run risk exposure of the small-size portfolio exceeds that of the large-size portfolio. Then, I look at the cross-sectional properties of the Fama-French industry portfolios, and the 25 Fama–French size and book-to-market ranked portfolios.

A final analysis done in this paper is to build portfolios based on the exposure of individual US stocks listed on NYSE, AMEX, or NASDAQ to the risk factors this paper proposed. The first step of this analysis is to build monthly risk factors. This is done by projecting the annual factors onto the space of Fama-French 25 ME/BM-sorted portfolios and keeping constant the annual weight throughout the time. I use the annual weights to build the monthly factors. The second step consists of computing the time-varying betas' using a rolling window approach – a minimum of 36 months and a maximum of 60 months past information. Then, I build the portfolios by sorting the stocks based on their betas into deciles. I monthly rebalance the portfolios. The long-short portfolios are formed by going long the last decile and going short the first decile. Additional long-short portfolios proposed in this analysis consist of going long firms that are positively exposed to the risk factors and going short firms that are negatively exposed. The last step is to compute the average premium and test the performance of the portfolios. I measure the performance of the portfolios using the alpha from the Fama-French three-factor model (see equation 1.27).

$$r_{i,t}^{ls} - rf_t = \alpha_i + \beta_1 mkt_t + \beta_2 hml_t + \beta_3 smb_t + \epsilon_{i,t} \quad i = 1, ..., n_{ls} \tag{1.27}$$

where $r_{i,t}^{ls} - rf_t$ is the excess return of the long-short portfolio i, α_i is the performance measure of the strategy i.

1.4 Findings

1.4.1 BY04 versus LRCCR

This part of the paper compares the LRCCR and LRR models in terms of replicating the observed equity premium, the volatility of the equity premium, and the risk-free rate. Here I calibrate the 17 parameters Θ=[ρ_x ψ_x ψ_d ν_{cc} ν ν_d σ_w σ ϕ_d δ γ ψ ν_α ρ_α σ_α π $\phi_{\alpha,d}$] to match the (share of) carbon consumption growth, the (share of) green consumption growth, dividend growth, the market return, and the risk-free rate means, variances, and (auto)correlations observed in the data. The calibration results are displayed in table 1.2 for both my setting and Bansal and Yaron (2004)'s setting (BY04 model). I present four sets of results: the full sample, the period around World War II, the period around the First Earth Day, and finally the post-Reagan election sample. This paper splits the results into four sets because returns react to news, and in earlier times, climate change or global warming was not a prominent issue. Therefore, we hypothesize that there is probably no big effect during the pre-Reagan election period. The paper uses President Reagan's election as a reference day because global public awareness of energy conservation and improvements in energy efficiency start around this time period.

The term Ψ_x tells us how detectable the long-run variable is. The results show that the long-run risk variable is more detectable than it is in the BY model during the 1956–2018 period, which is near the climate change events. The results in the table 1.2 show that there are long-run risks in volatility and carbon consumption growth: ν smaller and close to one, and ρ_x smaller and close to one. Overall, the risk aversion in our model is higher than the one in Bansal and Yaron (2004)'s setting but is within a reasonable range. This high value is related to the nature of the risk discussed in this paper (carbon risk). Furthermore, agents are more fearful of carbon risk than consumption risk because carbon risk will increase (amplify) consumption risk even more. The expression $\phi_{\alpha,d}$ functions as a leverage ratio on the share of carbon consumption growth during the period 1981–2018.

This paper simulates the time series of the model-implied carbon consumption growth, the share of carbon consumption growth, dividend growth, market return, and the risk-free rate. I present some quantiles of those series in tables 1.3 and A.4 for the four

Table 1.2: Calibrated parameters

	1930-2018		1930-1955		1956-1980		1981-2018	
	BY04	LRCCR	BY04	LRCCR	BY04	LRCCR	BY04	LRCCR
ρ_x	0.932	0.978	0.937	0.979	0.920	0.900	0.976	0.900
ψ_x	0.259	0.150	0.278	0.119	0.010	0.204	0.206	0.514
ψ_d	4.540	4.340	4.789	4.488	13.361	0.000	10.122	4.288
ν_x	9E-04	1E-03	1E-04	1E-03	-6E-05	2E-03	-2E-04	9E-04
ν	0.999	0.979	0.573	0.985	0.577	0.691	0.988	0.995
ν_d	0.001	-0.011	0.000	-0.025	-0.002	0.001	0.005	0.003
σ_w	5E-07	2E-08	1E-04	2E-07	7E-08	1E-05	4E-06	4E-06
σ	8E-03	3E-03	5E-04	4E-03	1E-03	1E-03	7E-04	9E-03
ϕ	2.294	3.378	2.354	3.734	321.850	10.056	0.792	1.019
δ	0.956	0.998	0.999	0.999	0.998	0.998	0.998	0.997
γ	7.074	12.290	9.878	10.084	15.940	23.016	6.063	8.732
ψ	1.379	1.487	3.018	1.495	1.574	1.235	1.503	1.486
$\bar{z}$	3.088	6.164	6.054	6.602	6.201	6.285	5.720	5.060
$\bar{z}_m$	5.344	3.981	5.153	3.522	4.754	5.696	12.820	5.548
ν_a		-3E-04		4E-05		-3E-04		-4E-04
ρ_a		0.455		0.480		-0.281		0.360
σ_a		0.006		0.006		0.014		0.004
π		1.344		0.897		3.328		0.626
ϕ_a		0.590		0.877		-0.294		1.305

The table reports the calibrated parameters for the different subsamples for both our setting (LRCCR) and the Bansal and Yaron (2004) setting (BY04).

samples. The quantiles 5% and 95% serve as the confidence intervals, and overall, the sample moments are within those intervals generated by our simulation in the preferred subsamples.

Table 1.3: Model-implied moments.

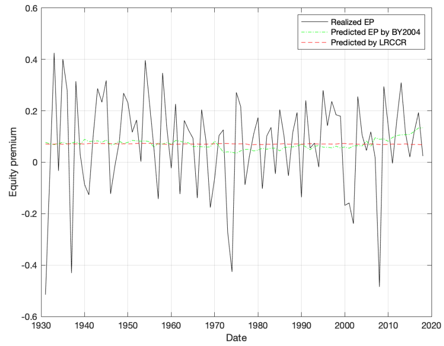
		$\sigma(z_m)$	EP	$E(R_f)$	$\sigma(r_{m,a})$	$\sigma(r_{f,a})$	$\rho(z_m)$
1930-2018							
	Data	0.512	0.067	0.002	0.193	0.002	0.928
BY2004	Mean	0.189	0.096	0.007	0.212	0.068	0.454
	5%	0.158	-0.029	-0.090	0.180	0.050	0.286
	50%	0.188	0.097	0.005	0.212	0.065	0.458
	95%	0.225	0.220	0.111	0.246	0.095	0.607
LRCCR	Mean	0.197	0.078	0.010	0.134	0.022	0.735
	5%	0.154	0.053	0.001	0.118	0.019	0.601
	50%	0.195	0.078	0.010	0.134	0.022	0.743
	95%	0.248	0.104	0.019	0.151	0.027	0.841
1981-2018							
	Data	0.415	0.072	0.011	0.162	0.011	0.890
BY2004	Mean	0.078	0.066	0.010	0.128	0.002	0.846
	5%	0.042	0.028	0.005	0.103	0.001	0.642
	50%	0.073	0.066	0.010	0.127	0.002	0.871
	95%	0.133	0.106	0.015	0.154	0.004	0.961
LRCCR	Mean	0.204	0.118	0.015	0.183	0.006	0.809
	5%	0.118	0.061	0.003	0.148	0.003	0.586
	50%	0.191	0.117	0.015	0.182	0.005	0.835
	95%	0.330	0.178	0.027	0.220	0.009	0.946

The table reports the model-implied moments (the equity premium (EP), the mean of the risk-free rate, the standard deviations of the log price-dividend ratio, the market return, and the risk-free rate, and the first-order autocorrelation of the log price-dividend ratio), alongside some-20 quantiles.

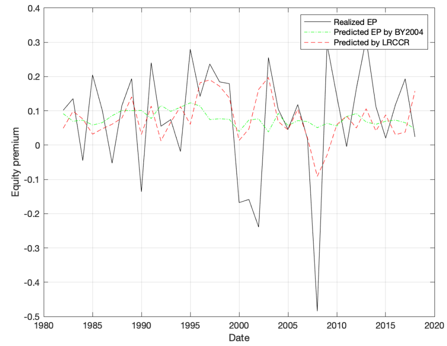
Now let us turn to the predictability implication of my model versus the one of Bansal and Yaron (2004) by comparing the predicted equity premium, consumption growth, and dividend growth rates and their realized counterparts. Most of the consumption capital asset pricing models find a constant risk premium: approximately constant predicted risk premium. However, during 1981–2018, a period of high carbon emissions risk, a long-run carbon consumption risks model finds a time-varying risk premium. My model performs much better than the usual long-run risk model in terms of replicating the documented time-varying risk-premium, consumption and dividend growths predictability, etc. (See Figure 1.5 and figure A.1 in the appendix A.6.) The difference is quite clear when I predict the macro-financial variables in the subsample, especially during the period 1981–2018, a period starting around the election of President Reagan, at time when climate actions began.

Figure 1.5: Realized versus predicted equity premium, consumption growth, and dividend growth.

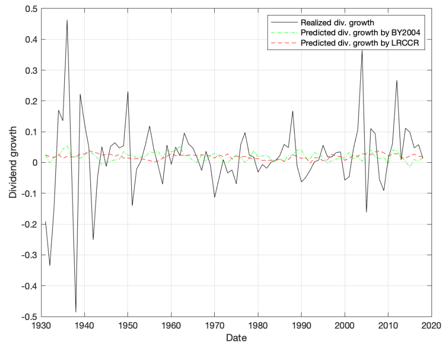
In this figure, I predict equity premium, consumption growth, and dividend growth using the long-run risk derived from my model and compared it to BY model.



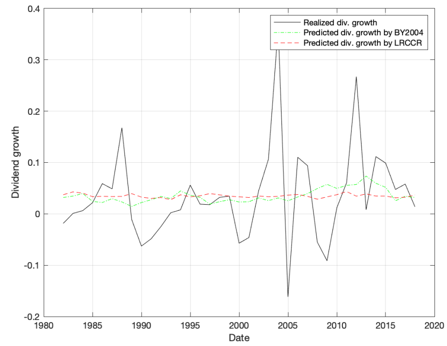
(a) Full sample: 1930-2018



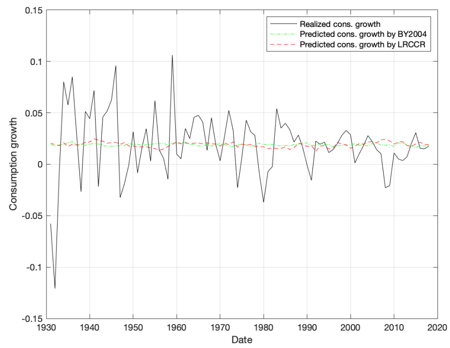
(b) 1981-2018



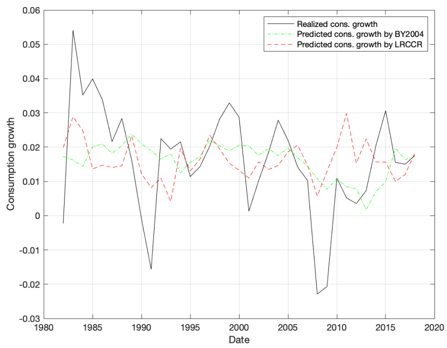
(c) Full sample: 1930-2018



(d) 1981-2018



(e) Full sample: 1930-2018



(f) 1981-2018

1.4.2 Comparative statics

This paper conducts comparative statics by computing the impulse response functions of three exogenous shocks: (*i*) shock on the expected carbon consumption growth, (*ii*) shock on the carbon consumption growth, and (*ii*) shock on the share of carbon consumption. As a result, one standard deviation negative shock to the expected carbon consumption –such shock could be a policy aiming to reduce the long-run carbon consumption– causes consumption growth to decrease by 5.5% for sixty months using the full sample parameter estimates. It decreases dividend growth, market return, and the risk free rate by 8%, 3.7%, and 4% respectively. Further analysis over different sub-periods shows that the impacts of environmental policies on asset prices and household consumption are bigger during periods of high climate change uncertainty (see Table 1.4, and Figures A.3 and A.2). In fact, the decrease in consumption growth is approximately 2%, 3%, and 11% during the periods 1930–1955, 1956–1980, and 1981–2018, respectively. The effects of the policy disappear after sixty periods –corresponding to five years. When considering a direct shock on the carbon consumption growth –such as policies aiming to reduce the short-run carbon consumption–, the effect on the consumption is mitigated and ambiguous. For example, one standard deviation negative shock to the short-run carbon consumption causes consumption growth to decrease by 0.04% for less than ten months using the full sample parameter estimates. The comparative statics may suggest the necessity of aiming for a policy that has a long-run effect than a short-run effect.

1.4.3 Risks and Price of risks

In this section, I compute the price of the four risk sources discussed in the model section: carbon consumption growth risk, the share of carbon consumption growth risk—which is correlated with the share of green consumption growth risk—long-run risk, and volatility risk. The most important result from table 1.5 is the consistent sign of the contribution of volatility risk in the equity premium under my model. The market is negatively exposed to volatility risk in every sample I considered.

Table 1.4: Comparative statics : Impulse Response Function

Comparative statics : Impulse Response Function In this table, I show the impulse response functions of consumption growth, carbon consumption growth, share of carbon consumption growth, price dividend ratio, market return, and risk free rate following three shocks: shock on the expected carbon consumption growth, shock on the carbon consumption growth, and shock on the share of carbon consumption.

	ϵ_x shock	ϵ_{cc} shock	ϵ_α shock
		1930-2018	
Δcc	5.51	1.29	0.00
$\Delta \alpha_{cc}$	0.00	1.25	1.49
Δd	7.92	1.02	1.21
r_m	3.72	-0.41	-0.49
r_f	4.02	-0.41	-0.49
		1930-1955	
Δcc	2.02	0.35	0.00
$\Delta \alpha_{cc}$	0.00	0.61	1.11
Δd	7.53	0.54	0.98
r_m	1.32	-0.20	-0.36
r_f	1.35	-0.20	-0.36
		1956-1980	
Δcc	3.44	1.47	0.00
$\Delta \alpha_{cc}$	0.00	5.03	1.01
Δd	17.17	-0.56	-0.11
r_m	1.00	0.45	0.09
r_f	1.09	0.45	0.09
		1981-2018	
Δcc	10.71	1.85	0.00
$\Delta \alpha_{cc}$	0.00	2.54	0.73
Δd	11.52	2.36	0.68
r_m	6.51	-0.60	-0.17
r_f	7.04	-0.60	-0.17

Table 1.5: Market prices of risks and effects on the risk premium

		λ	β	effect	λ	β	effect
		1930-2018			1930-1955		
BY04	srr	7.07	0.00	0	9.88	0.00	0
	lrr	14.47	5.58	+	40.61	8.17	+
	vr	-2564.24	-7723.52	+	-1884.32	-515.00	+
LRCCR	$\alpha risk$	-21.93	1.59	−	-18.75	2.18	−
	srr	-17.19	2.13	−	-6.74	1.96	−
	lrr	73.78	10.16	+	50.61	7.28	+
	vr	-122914.44	-14400.98	+	-79112.00	-6155.20	+
		1956-1980			1981-2018		
BY04	srr	15.94	0.00	0	6.06	0.00	0
	lrr	1.92	37.37	+	40.87	1.09	+
	vr	-273.13	1687.23	−	-51947.16	5284.64	−
LRCCR	$\alpha risk$	-18.15	-0.41	+	-13.22	2.40	−
	srr	-37.37	-1.35	+	0.46	1.50	+
	lrr	44.47	18.41	+	38.93	2.04	+
	vr	-5168.90	-1975.90	+	-66622.82	-4374.95	+

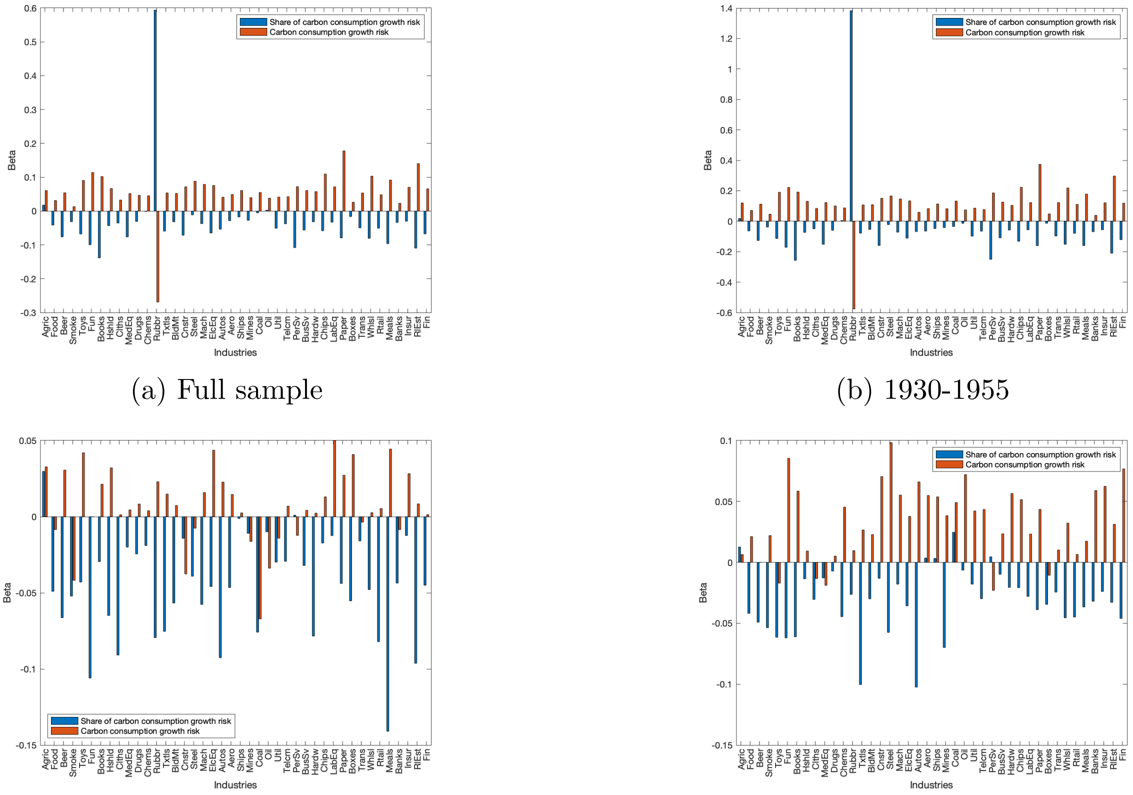
1.4.4 Cross-sectional implications

As evident in figure 1.6, I cannot classify the industries based on their betas until 1955. All of the industries are positively and negatively exposed to the carbon consumption growth risk and the share of the carbon consumption growth risk, respectively. One exception is the rubber and plastic products industry, which is negatively and positively exposed to the carbon consumption growth risk and the share of the carbon consumption growth risk, respectively. Starting in 1956, the risk factors start to affect the industries differently. This result is interesting because it tells us that our risk factors are eventually able to identify industries, and firms that pollute the most based on their levels of risk exposure at a time when it matters the most.

In tables 1.6 and 1.7, this paper reports the risk-premium estimates ($\hat{\gamma}$) and t-statistics (*t-ratio*) associated to each risk factor. I use multiple risk factors: Fama and French (1993) three-factors, consumption growth risk, carbon and green consumption growth risks, the growth risks of the share of carbon and green consumption out of total consumption. The risk premium estimates of the market factor (*mkt*) are consistently negative for both industry portfolios and Fama–French size and book-to-market sorted portfolios. The market factor is negatively priced (see table 1.7) at the 5% level and the risk premium ranged from -13.14% to -8.29%. That finding corroborates with past empirical studies and contradicts theoretical evidence[9]. The value minus growth factor (*hml*) is priced in any of my specifications. In particular, the associated risk premium is consis-

[9] Glosten et al. (1993), Whitelaw (2000), Han (2011), etc.

Figure 1.6: Exposure of industries to carbon consumption risks: β's



(a) Full sample

(b) 1930-1955

(c) 1956-1980

(d) 1981-2018

tently and significantly negative at 5% level using Fama-French industry portfolios (see table 1.6). However, the risk premium is consistently and significantly positive at 1% level using Fama–French size and book-to-market sorted portfolios (see table 1.7). The later confirms Kan et al. (2013) findings.

Among my risk factors, only carbon consumption growth risk is negatively priced using Fama-French industry portfolios at 10% level. My risk factors reliably explain the cross-section of size and book-to-market sorted portfolios. In particular, carbon consumption growth risk (Δcc) and the share of carbon consumption growth risk ($\Delta \alpha_{cc}$) are negatively priced while green consumption growth risk (Δgc) and the share of green consumption growth risk ($\Delta \alpha_{gc}$) are positively priced at 1% level.

I investigate the contribution of my factors in explaining the cross-section of industry portfolios and of size and book-to-market sorted portfolios. I did it by testing if the cross-sectional R^2 of Fama and French (1993) three-factors model is equal to the cross-sectional R^2 of an alternative model adding new factors to the three-factors (FF3) model. Findings are reported in table A.5. Three alternative specifications outperform FF3 model at 5% level and two outperform at 10% level. Under potential misspecification, only two of my alternative models outperform at 10% and none at 5%.

Table 1.6: Industry portfolios

	mkt	hml	smb	Δc	Δcc	$\Delta\alpha_{cc}$	Δgc	$\Delta\alpha_{gc}$	R^2
$\hat{\gamma}$	-0.0259				-0.0084	-4.1E-06			
t ratio	-1.0794				-1.6910	-0.0327			0.059
$\hat{\gamma}$	-0.0253			-0.0119					
t ratio	-1.0591			-2.4436					0.104
$\hat{\gamma}$	-0.0247	-0.0404	-0.0059						
t ratio	-1.0205	-2.2953	-0.3763						0.095
$\hat{\gamma}$	-0.0245	-0.0423	-0.0053		-0.0089				
t ratio	-1.0151	-2.3947	-0.3356		-1.7862				0.122
$\hat{\gamma}$	-0.0254	-0.0404	-0.0059			-3.2E-05			
t ratio	-1.0470	-2.2969	-0.3709			-0.2553			0.097
$\hat{\gamma}$	-0.0222	-0.0441	-0.0078	-0.0124					
t ratio	-0.9181	-2.4957	-0.4939	-2.5408					0.170
$\hat{\gamma}$	-0.0239	-0.0425	-0.0053		-0.0089	-1.2E-05			
t ratio	-0.9850	-2.4017	-0.3362		-1.7894	-0.0916			0.123
$\hat{\gamma}$	-0.0244	-0.0424	-0.0053				-0.0055	0.0034	
t ratio	-1.0067	-2.3937	-0.3377				-0.6161	0.4078	0.122

This table reports the risk-premiums ($\hat{\gamma}$) and t-statistics (*t-ratio*) associated to each risk factor. I use multiple factors: Fama and French (1993) three-factors, consumption growth risk, carbon and green consumption growth risks, the growth risks of the share of carbon and green consumption out of total consumption. The models are estimated using annual returns on 42 industry portfolios. The data are from 1930 to 2018. This table also reports the cross-sectional R^2 in the last column.

Table 1.7: Fama-French 25 ME/BM- sorted portfolios

	mkt	hml	smb	Δc	Δcc	$\Delta\alpha_{cc}$	Δgc	$\Delta\alpha_{gc}$	R^2
$\hat{\gamma}$	-0.0944				-0.0110	-0.0007			
t ratio	-3.1680				-2.0736	-4.0674			0.191
$\hat{\gamma}$	-0.0829			-0.0060					
t ratio	-2.7848			-1.1344					0.069
$\hat{\gamma}$	-0.1224	0.0406	0.0248						
t ratio	-4.0071	2.5795	1.7063						0.250
$\hat{\gamma}$	-0.1147	0.0407	0.0245		-0.0085				
t ratio	-3.6605	2.5895	1.6833		-1.6078				0.259
$\hat{\gamma}$	-0.1222	0.0420	0.0199			-0.0006			
t ratio	-4.0001	2.6669	1.3647			-3.6273			0.350
$\hat{\gamma}$	-0.1170	0.0406	0.0251	-0.0060					
t ratio	-3.7180	2.5835	1.7232	-1.1383					0.254
$\hat{\gamma}$	-0.1259	0.0420	0.0198		-0.0106	-0.0006			
t ratio	-3.9967	2.6673	1.3551		-1.9972	-3.6567			0.351
$\hat{\gamma}$	-0.1314	0.0421	0.0209				0.0280	0.0377	
t ratio	-4.1437	2.6741	1.4318				2.9838	3.8475	0.343

This table reports the risk-premiums ($\hat{\gamma}$) and t-statistics (*t-ratio*) associated to each risk factor. I use multiple factors: Fama and French (1993) three-factors, consumption growth risk, carbon and green consumption growth risks, the growth risks of the share of carbon and green consumption out of total consumption. The models are estimated using annual returns on the 25 Fama–French size and book-to-market ranked portfolios. The data are from 1930 to 2018. This table also reports the cross-sectional R^2 in the last column.

The results of the firms-level analysis are shown in Tables 1.8 and A.6. There is no profitable strategy –all significant α's are negative– that outperformed the FF3 model benchmark return using the factors constructed by this paper. However, the individual factor premium of the strategy going long/short extreme deciles constructed based on carbon consumption's betas is above the average factor premiums of SMB and HML using the full sample (table A.6). That average premium is significant at 10% level.

Table 1.8: Alphas (%) of the proposed long-short portfolios.

This table shows the performance of the portfolios measured by the alpha from the Fama-French three-factor model: $r^{ls}_{i,t} - rf_t = \alpha_i + \beta_1 mkt_t + \beta_2 hml_t + \beta_3 smb_t + \epsilon_{i,t}$ $i = 1, ..., 8$ where $r^{ls}_{i,t} - rf_t$ is the excess return of the long-short portfolio i, α_i is the performance measure of the strategy i. It reports the α's for eight strategies. The first four columns' strategies long/short extreme deciles while the last four long/short firms that have positive/negative betas.

	Δcc	$\Delta \alpha_{cc}$	Δgc	$\Delta \alpha_{gc}$	$s(\Delta cc)$	$s(\Delta \alpha_{cc})$	$s(\Delta gc)$	$s(\Delta \alpha_{gc})$
	January 1930 - June 2018							
α_i	0.33	-0.66***	0.25	-0.28	-0.19***	-0.30***	-0.21***	-0.24***
	(0.23)	(0.22)	(0.22)	(0.21)	(0.07)	(0.07)	(0.07)	(0.07)
	January 1930 - December 1980							
α_i	0.32	-0.52**	0.45*	-0.46**	-0.18**	-0.22**	-0.12	-0.26***
	(0.26)	(0.25)	(0.26)	(0.22)	(0.08)	(0.10)	(0.08)	(0.09)
	January 1980 - June 2018							
α_i	0.29	-0.68*	0.09	-0.22	-0.24**	-0.41***	-0.34***	-0.13
	(0.39)	(0.37)	(0.38)	(0.37)	(0.12)	(0.11)	(0.11)	(0.11)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

1.5 Conclusion

This paper tackles the long-run carbon consumption risks model by allowing both long-run risks in mean and volatility. We use an Epstein-Zin utility function to disentangle the risk aversion coefficient and because of its ability to deal with the climate change thematic. This paper finds empirical support for the long-run risks model in the context of carbon-green consumption. Three state variables completely define the other variables in the economy. To sum up, our long-run carbon consumption risks model solves the equity premium, volatility, and risk-free rate puzzles by decomposing consumption growth into two components: the growth rate of the carbon consumption component and the growth rate of the share of green consumption out of total consumption. Our model setting increases the ability of investors to detect long-run risk; namely, investors can profit from this risk by using climate change news. Also, our risk factors explain the cross section of industries and firms. Thus, this paper recommends using the carbon risk measures we computed to identify industries or firms that pollute the environment the most and to construct an investment strategy that minimizes/maximizes a long-term environmental criterion. However, this paper does not find enough evidence about using the risk factors provided to build investment strategies that easily beat a benchmark portfolio which return is given by the FF3 model.

Further research can use other proxies for the green component in the consumption decomposition and conduct the same analysis. One such proxy could be R&D expenses of carbon-intensive firms allocated to green technology or the revenue from selling Solar Renewable Energy Certificates.

Chapter 2

Asset Pricing with Nonlinear Principal Components*

2.1 Introduction

The search for a parsimonious stochastic discount factor (SDF) that can explain a large cross-section of equity returns is central to empirical asset pricing. The recent contribution of Kozak et al. (2020) shows that a large cross-section of characteristics-based portfolios can be shrunk to a few principal components that make up a SDF with a robust predictive out-of-sample pricing performance. This departs from the previous literature, where a limited number of factors predicted the variation of a given cross-section of characteristics-based portfolios. As this cross-section enlarged and new characteristics emerged, the number of factors increased from three in (Fama and French (1993)) to four in (Hou et al. (2015)), five in (Fama and French (2015)), and six in (Barillas and Shanken (2018)). Kozak et al. (2020) show that restricting the SDF to a few characteristics-based factors does not adequately capture the cross-section of expected returns. A sparse SDF with a few high-variance principal components produces a good and robust out-of-sample fit of the cross-section of expected returns.

The above-mentioned achievements make clear the importance of performing transformations of the original set of raw returns in order to obtain a robust SDF. In this paper, we move one step further by studying how changing the metric in which raw information is transformed in (potential) SDF factors affects this SDF's pricing performance on a fixed cross section of returns. While Kozak et al. (2020) use a Bayesian method based on a quadratic criterion we adopt an entropic criterion, which brings novel statistical properties to the extracted factors. We build on the recent theoretical developments of Gunsilius and Schennach (2021) who use a multivariate additive entropy decomposition to generalize the principal component analysis (PCA) to a nonlinear setting. Their non-

*Co-authored with René Garcia and Caio Almeida. I am indebted to my advisor, René Garcia for his invaluable guidance and support.

linear principal components analysis delivers truly independent factors (as opposed to the uncorrelated factors of PCA) that maximize the percent of entropy information from the original cross-section of raw returns that is explained by the nonlinear factors.

Our main empirical contribution is to show that, for different fixed cross-sections of returns, when a small number of nonlinear principal components is allowed to complement/substitute factors on an SDF based on linear principal components, the nonlinear SDF consistently outperforms the linear specification and with fewer factors. To better understand the additional value of nonlinear principal components in pricing the cross-section of returns, we apply the new methodology to the Fama-French 25 ME/BM-sorted portfolios. While the Fama-French three-factor linear model has been the workhorse of the asset pricing literature, it did not explain well the returns of extreme portfolios, especially the small-growth one, where nonlinear relations between portfolios and factors may be present. Next, we explore the set of fifty anomaly portfolios built by Kozak et al. (2020) using individual stock characteristics to assess the predictive ability of a stochastic discount factor combining both linear and nonlinear factors. Lastly, we use the big data set of 2600 portfolios proposed by Kozak et al. (2020), which includes the fifty raw characteristic excess returns plus 2550 interaction terms obtained by crossing the characteristics of the stocks (two by two and adding the third power of each characteristic) and aimed at capturing nonlinearities. Adding nonlinear principal components to linear factors increases substantially the out-of-sample R^2's for the different cross-sections of returns under consideration.

The numerical procedure used to extract the nonlinear principal components proceeds in several steps. We start with n variables that are potential predictors of future returns and extract n linear principal components in the usual way. We then select the k linear factors having the largest eigenvalues (variances) and apply the algorithm of Gunsilius and Schennach (2021) to capture nonlinear forms of dependence through truly independent factors. The approach relies on the theory of Brenier maps Brenier (1991), which are a generalization of monotone functions in multivariate settings, and on the use of entropy[1] to determine the principal nonlinear components that capture most of the information content of the data, instead of variance for linear principal components. Another important ingredient is a multivariate additive decomposition of the entropy into one-dimensional contributions.

Entropy as a measure of dispersion has received considerable attention in the asset pricing literature. The main focus has been on extracting SDFs from observed asset prices in the spirit of Hansen and Jagannathan (1991) who minimize the variance of the SDF subject to asset pricing restrictions. Minimizing the entropy involves higher moments of the distribution of asset returns and captures nonlinearities in the pricing kernel or non-Gaussianity in returns. Stutzer (1995) suggests a nonparametric bound to test

[1]See Shannon (1948), Kullback (1997), Csiszar (1991), and the other references cited in Gunsilius and Schennach (2021).

asset pricing models based on entropy minimization, while Bansal and Lehmann (1997) propose a related entropic bound that is obtained by maximizing the growth portfolio. Backus et al. (2011) tests disaster-based models based on this entropic bound. Several papers derive pricing kernels based on entropy. Alvarez and Jermann (2005) provide a decomposition of the pricing kernel into permanent and transitory components, while Ghosh et al. (2017) propose a factorization of the SDF into an observable component (a parametric function of consumption) and an unobservable nonparametric one. Backus et al. (2014) characterize the pricing kernel entropy and its dynamics for several representative agent models. Chen et al. (2020b) use a statistical measure of discrepancy that extends relative entropy to recover information about investor beliefs embedded in forward-looking asset prices in conjunction with asset pricing models. Almeida and Garcia (2012, 2017) minimize a large class of divergence measures which includes entropy under asset pricing restrictions and derive information bounds as well as misspecification measures.

Since the nonlinear factors are not tradable by nature, we construct mimicking portfolios to extract tradable factors to be priced alongside with the linear principal components. For robustness purposes, we proceed in three manners. First, we performed a linear regression of the nonlinear factors on the fifty anomaly excess returns including a constant term. Second, we add one more asset, the CRSP value-weighted index, in the previous (first) regression. Third, we add an option on the market, to the previous (second) regression. In this third regression, we approximate the nonlinear principal components using a piecewise function to take into account their nonlinearities (see Glosten and Jagannathan (1994), and Diez De Los Rios and Garcia (2011)). Therefore, the mimicking portfolios are the predicted nonlinear factors from the regressions. We then use these mimicking portfolios along with the linear factors or linear principal components to estimate the stochastic discount factor or to predict future expected returns under the set up of Kozak et al. (2020). In the final step of our methodology, we regress the expected returns of different sets of tradable factors on the covariance matrix of different set of factors under Elastic-Net and Ridge penalties, and then, assess the accuracy of these regressions by computing the out-of-sample and in-sample cross-sectional R^2. We use the 3-fold cross-validation procedure of Kozak et al. (2020) to compute the out-of-sample R^2.

This paper is related to three strands of literature. First, the vast literature on nonlinear principal components. Papers here include Kramer (1991), Schölkopf et al. (1998), Roweis and Saul (2000), Lee and Verleysen (2007), Chen et al. (2009), Lawrence (2012), and Damianou et al. (2021) among others. Recall that traditional principal components are extracted under the assumption of independence and stationarity of the raw random variables, which are then rotated to obtain uncorrelated linear factors chosen to maximize the explained variance of the original variables. While all the above-mentioned methods use variations and / or generalizations of the traditional principal components method which go from relaxing independence (Chen et al. (2009)) to applying traditional PCA to an augmented features' space via "the kernel trick" (Schölkopf et al. (1998)), they all obtain factors that maximize the explained variance of the original raw data using a quadratic criterion. In contrast, we build on Gunsilius and Schennach (2021) who find factors that are truly independent by construction and that maximize an aggregate measure of the entropy of the original raw random variables. In this context, our paper is the first to empirically test these entropic dynamic factors in an asset pricing application involving the identification of a SDF that prices the cross-section of stocks.

Second, this paper is related to the new growing literature on machine learning asset pricing models (Feng et al. (2018), Nakagawa et al. (2019), Chen et al. (2020a), and Fang and Taylor (2021)). It provides a test for the effectiveness of using an alternative dimension reduction technique (based on entropy as a metric) to price the cross-section of stock returns. Third, this paper is also related to the strand of literature on the stochastic discount factor estimation using a given set of factors. Papers here include Fama and French (1993), Hou et al. (2015), Fama and French (2015), Barillas and Shanken (2018) and Kozak et al. (2018). While all these models bet on linear factor models we show that obtaining nonlinear dynamic factors can bring additional valuable information to price the cross-section of stock returns.

Our paper is also closely related to Gunsilius and Schennach (2021) and Kozak et al. (2020) in terms of methodology. However, there are key differences between this paper and theirs. Compared to Gunsilius and Schennach (2021) –which is mainly theoretical and did a simple application to predict bond excess returns using directly non tradable factors (nonlinear principal components) conjointly with tradable factors–, our paper sheds light on how to better adapt empirically the theory of truly independent nonlinear factors to an asset pricing context. We use the stock market as opposed to the bond market and the (tradable) mimicking portfolios analysis as opposed to the non tradable portfolios analysis in Gunsilius and Schennach (2021). Compared to Kozak et al. (2020), our analysis uses a set of truly independent nonlinear factors and linear factors. This hybrid method delivers compelling out-of-sample performance measured by the R^2.

The remainder of the paper is organized as follows. Section 2.2 explains the methodology to extract the independent nonlinear components and to construct the stochastic discount factor to price the various sets of portfolios. Section 2.3 describes the construction of the data. We report the results of our analysis in Section 2.4 and conclude in Section 2.5.

2.2 Methodology

We first describe the steps to follow to construct the nonlinear factors, then we specify the estimation procedure of the stochastic discount factor.

2.2.1 Nonlinear Principal Components

Let us consider n portfolios whose excess returns are stacked in a $1 \times n$ vector $r = (r_1, r_2, ..., r_n)$. One would like to reduce the dimensionality of the space of these n portfolios to $k < n$ factors. The most common way is to take the first k linear principal components. This dimension reduction operates by finding successively the linear combination of the portfolio returns that explains the largest share of the variance-covariance matrix of the original set of portfolios, with the condition that each successive principal component is uncorrelated with the previous ones. The intuition is that we search for a line along which the points are the most dispersed, with the variance as a measure of dispersion. However, the principal component analysis can be generalized to explore nonlinear data representations. Gunsilius and Schennach (2021) propose to use entropy, as another concept of dispersion, to determine the most informative principal nonlinear components. Moreover, the method delivers independent instead of uncorrelated factors.

Let us suppose that r has a density function denoted $g(r)$. The idea of extracting truly independent nonlinear factors is to find a map $T : \mathbb{R}^n \longmapsto \mathbb{R}^n$ transforming $g(r)$ into a target density $\Phi(\tilde{r})$ where $\tilde{r} = T(r)$. The choice of this pre-specified density Φ is useful to find truly independent factors as we will choose a density that factors as a product of the marginal densities. Therefore, we choose Φ to be a multivariate normal density function among other possible choices. The change of variable formula yields an expression of the original density function in terms of the target density function and the Brenier map as follows :

$$g(r) = \Phi(T(r))det(\frac{\partial T(r)}{\partial r'}) \tag{2.1}$$

First, we need to estimate the mapping function T by minimizing the distance between a nonlinear transformation of the data $T(r)$ and the original data r. We want to take into account a possible nonlinear relationship between the portfolios and yet, we do not want to depart too much from the original portfolios. Hence, T minimizes the following optimization problem:

$$
\begin{aligned}
\min_{T} \quad & \int ||T(r) - r||^2 g(r)dr \\
\text{s.t.} \quad & \int_A g(r)dr = \int_{T^{-1}(A)} \Phi(\tilde{r})d\tilde{r}, \ A \subset \mathbb{R}^n \\
& g(r) = \Phi(T(r))det(\frac{\partial T(r)}{\partial r'}) \\
& T \text{ is bijective} \\
& T \text{ is measurable} \\
& T \text{ is approximately differentiable}
\end{aligned} \tag{2.2}
$$

The known solution of this minimization problem (Monge-Kantorovich-Brenier optimal transportation problem) is $T(r) = \frac{\partial C(r)}{\partial r}$, where C is a convex function. The function C can be estimated using a grid point procedure or an approximation procedure. This paper uses the grid point procedure. Second, we extract k eigenvectors $e = (e_1, e_2, ..., e_k)$ corresponding to the k largest eigenvalues of $\tilde{J}$ defined by :

$$\tilde{J} = -\int g(r)log\frac{\partial T(r)}{\partial r'}dr \tag{2.3}$$

Finally, the i^{th} nonlinear principal component is defined by : $NLF_i = T(r)e_i$ (versus $LF_i = r \times \tilde{e}_i$[2] in the linear case). This is a nonlinear transformation of the original portfolio returns because T is a nonlinear function unless r is a Gaussian process. The nonlinear transformation of the portfolio returns implies that the new factors, $NLF = (NLF_1, NLF_2, ..., NLF_k)$[3] are not tradable in the sense that their returns cannot be obtained as a linear combination of the original portfolios of assets. We therefore resort to the usual procedure of forming a mimicking portfolio for each nonlinear factor -in order to see which asset will be long and short - before the estimation of the stochastic discount factor. We explain in Section 2.3.2 the various regression methods we used to obtain the mimicking portfolios.

2.2.2 Stochastic Discount Factor estimation procedure

In this section, F_t stands for all factors –either the t^{th} row of the raw characteristic returns matrix (RC), or the t^{th} row of the linear principal components matrix (LF), or the t^{th} row of the nonlinear principal components matrix (NLF), or the t^{th} row of the combined matrix. We assume that the Stochastic Discount Factor (SDF) is an affine function of the factors, as follows :

$$SDF_t = 1 - \lambda'(F_t - \mu) \tag{2.4}$$

[2] $\tilde{e}$ are the eigenvectors of $Cov(r)$

[3] The i^{th} nonlinear factor is a vector $NLF_i = (NLF_{i,1}, NLF_{i,2}, ..., NLF_{i,t}, ...)$, written in times series.

where λ is a $K \times 1$ vector of factor loadings, F_t is a $K \times 1$ vector of risk factors at time t and $\mu = \mathbb{E}(F_t)$ is a $K \times 1$ vector of factors' mean. The stochastic discount factor should satisfy the law of one price:

$$\mathbb{E}(SDF_t \times F_t) = 0 \tag{2.5}$$

$\mathbb{E}(.)$ is the mathematical expectation. Equation 2.5 is in line with the characteristics-based factor model literature.

The naive sample estimator of λ is $\hat{\lambda} = \bar{\Sigma}^{-1}\bar{\mu}$[4]. This naive estimator is imprecise due to uncertainty about μ and Σ. However, the principal origin of imperfection is μ –the factor means since we can use a robust estimator for Σ (see Ledoit and Wolf (2004a), Ledoit and Wolf (2004b), Kozak et al. (2020)). Therefore, we make two additional assumptions about the factors: first, we suppose that μ is random and follows a normal distribution, and second, we consider that $\Sigma = Cov(F_t)$ is known.

$$\mu \sim \mathcal{N}(0, \frac{\kappa^2}{\tau}\Sigma^\eta) \quad , \ \tau = tr[\Sigma] \tag{2.6}$$

where κ is a scale parameter, η is a shape parameter which we set its value to 2, and $\mathcal{N}(0, \frac{\kappa^2}{\tau}\Sigma^\eta)$ is the normal distribution of mean 0 and variance $\frac{\kappa^2}{\tau}\Sigma^\eta$. Because we also suppose that there is no near-arbitrage opportunities, we want the Sharpe ratio of high-eigenvalue principal components (PCs) to be higher than the Sharpe ratio of the low-eigenvalue PCs (which is economically plausible since the latter do not bring much risk premium, as emphasized in Kozak et al. (2020)).

We follow Kozak et al. (2020) procedure to estimate the stochastic discount factor. Basically, λ solves the following minimization problem:

$$\hat{\lambda} = arg\min_{\lambda}(\mu - \Sigma\lambda)'\Sigma^{-1}(\mu - \Sigma\lambda) + \gamma_1\sum_{i=1}^{K}|\lambda_i| + \gamma_2\lambda'\lambda, \tag{2.7}$$

that is we minimize the HJ-distance subject to an Elastic-net/Ridge constraint[5]. Under the assumption that $\eta = 2$, $\gamma_1 = 0$, and therefore $\gamma_2 = \frac{\tau}{\kappa^2 T}$, the expected maximum squared Sharpe ratio is equal to the squared scale parameter :

$$\mathbb{E}(\mu\Sigma^{-1}\mu) = \kappa^2 \tag{2.8}$$

Under the ridge shrinkage hypothesis $\gamma_1 = 0$, we obtain

$$\hat{\lambda} = (\Sigma + \gamma_1\mathbb{I})^{-1}\mu$$

$\mathbb{I}$ is a $K \times K$ identity matrix. Under the Elastic-Net shrinkage hypothesis, we use the

[4] $\bar{\Sigma}$ is the sample estimation of the covariance matrix and $\bar{\mu}$ is the sample factors' mean.
[5] γ_1 and γ_2 are the tuning or shrinkage parameters.

Least Angle Regression (LAR-EN) algorithm[6] to estimate λ.

The shrinkage parameters γ_2 or (γ_1 and γ_2) are optimally chosen using the out-of-sample R-squared constructed by cross-validation as in Kozak et al. (2020). First, we set a grid on the shrinkage parameters γ_1, and γ_2. Second, we divide the sample into H equal subsamples. Third, for each possible pair of γ_1 and γ_2, we compute $\hat{\lambda}$ by using $H-1$ of these subsamples. Then, we evaluate the out-of-sample fit of the resulting model on the single withheld subsample by computing the out-of-sample R-squared (R^2_{oos}) as

$$R^2_{oos} = 1 - \frac{\left(\mu_2 - \tilde{\Sigma}_2\hat{\lambda}\right)'\left(\mu_2 - \tilde{\Sigma}_2\hat{\lambda}\right)}{\mu_2'\mu_2} \tag{2.9}$$

where μ_2 and $\tilde{\Sigma}_2$ are respectively the sample mean and covariance of the factors from the withheld subsample. We do this exercise H times and for each time, we treat a different subsample as the out-of-sample data. Finally, we define the cross-validated R^2_{cv-oos} as the average of the R^2_{oos} across these H estimates and choose γ_1 and γ_2 that generates the highest R^2_{cv-oos} as the optimal values.

2.3 Data

As mentioned in the introduction, the empirical part of this paper employs three data sets. First, we use the Fama-French 25 ME/BM-sorted (FF25) portfolios dowloaded from Kenneth R. French website. The two other data sets are built using individual stock characteristics. We start by all the firms' stocks available on the Center for Research in Security Prices (CRSP) and take the accounting data from Compustat. The data from CRSP are monthly/daily and the one from Compustat are quarterly. Our final data is a set of daily/monthly returns spanning the period from November 1973 to December 2019. For each date t and from each stock $s \in 1, 2, ..., n_t$, we build fifty stock-characteristic portfolios (see Table B.1) following the common definition of anomalies (Novy-Marx and Velikov (2016), Kozak et al. (2020)) : $\left(x^i_{s,t}\right)_{s\in 1,2,...,n_t;\ i\in 1,2,...,50;\ t\in 1,2,...,T}$, where n_t is the number of stocks at time t for which we can calculate the anomaly variable. Following Freyberger et al. (2020) and Kozak et al. (2020), we perform a rank-transformation denoted $rx^i_{s,t}$ before normalizing that rank-transformed characteristic to obtain the final zero-investment long-short portfolios denoted $z^i_{s,t}$. First, we rank all stocks for which data are available based on $x^i_{s,t}$ for each i, t. Second, we compute $rx^i_{s,t}$ and $z^i_{s,t}$ as follows :

[6] See the appendix for the algorithm.

$$rx^i_{s,t} = \frac{rank(x^i_{s,t})}{1+n_t} \tag{2.10}$$

$$z^i_{s,t} = \frac{rx^i_{s,t} - \frac{1}{n_t}\sum_{s=1}^{n_t} rx^i_{s,t}}{\sum_{s=1}^{n_t} |rx^i_{s,t} - \frac{1}{n_t}\sum_{s=1}^{n_t} rx^i_{s,t}|} \tag{2.11}$$

The anomalies are monthly for anomalies using CRSP variables and quarterly for anomalies whose calculations use accounting variables. To obtain daily factor returns, we assumed that the anomalies take the same values for each day within the month or the quarter. Third, the raw characteristic factors are obtained by : $RC_t = Z'_{t-1}R_t$ where Z_t is a n_t-by-50 matrix containing the $z^i_{s,t}$ for all s, i and R_t is a n_t-by-1 vector of daily returns from CRSP. Before doing this interaction, we remove all small capitalization stocks with capitalization under 0.01% of the aggregate market capitalization for each t from the data. Furthermore, we orthogonalized each factor returns with respect to the CRSP value-weighted index return using β's estimated with the full sample. Then, we rescaled the portfolio returns to have their standard deviations equal to the in-sample standard deviation of the excess returns on the CRSP value-weighted index returns which we took as the market index. We computed the excess returns using the one-month Treasury bill rate.

2.3.1 Interactions

We add interaction terms to the second data set to constitute the third data set. The aim of the use of this database is to compare the nonlinearity introduced by Kozak et al. (2020), which requires a very high-dimensional data set (2,600 factors), to the empirical performance of the nonlinearity introduced by Gunsilius and Schennach (2021), which require less nonlinear factors. The interaction-term weights on the individual stocks are constructed as follows:

$$z^{ij}_{s,t} = \frac{z^i_{s,t}z^j_{s,t} - \frac{1}{n_t}\sum_{s=1}^{n_t} z^i_{s,t}z^j_{s,t}}{\sum_{s=1}^{n_t} |z^i_{s,t}z^j_{s,t} - \frac{1}{n_t}\sum_{s=1}^{n_t} z^i_{s,t}z^j_{s,t}|} \tag{2.12}$$

$$z^{ii}_{s,t} = \frac{(z^i_{s,t})^2 - \frac{1}{n_t}\sum_{s=1}^{n_t}(z^i_{s,t})^2}{\sum_{s=1}^{n_t} |(z^i_{s,t})^2 - \frac{1}{n_t}\sum_{s=1}^{n_t}(z^i_{s,t})^2|} \tag{2.13}$$

$$z^{iii}_{s,t} = \frac{(z^i_{s,t})^3 - \frac{1}{n_t}\sum_{s=1}^{n_t}(z^i_{s,t})^3}{\sum_{s=1}^{n_t} |(z^i_{s,t})^3 - \frac{1}{n_t}\sum_{s=1}^{n_t}(z^i_{s,t})^3|} \tag{2.14}$$

2.3.2 Nonlinear principal components

As stated in the methodology section, this paper uses a grid-point procedure to estimate the Brenier map needed to compute the nonlinear factors. We extract the nonlinear factors using either the fifty raw characteristics data or the Fama-French 25 portfolios. To reduce the computation burden, we adopt a hybrid procedure. First, one extracts the linear principal components, henceforth LF from the fifty raw characteristics (or the Fama-French 25 portfolios). Second, we compute k nonlinear principal components, hereafter NLF from the first k linear principal components $(LF_1, LF_2, ..., LF_k)$[7]. The rationale for this approach rests on the premise that the nonlinearity comes from the linear factors with the highest eigenvalues, the ones that capture the most information.

As mentioned before, we need to reconcile the statistical factor extraction and the financial factors extraction by constructing portfolios mimicking NLF. For robustness purposes, we consider three regression strategies for constructing the mimicking portfolios. The first two regressions estimate the mimicking portfolios in the usual way. It consists in projecting the factors on a set of basis assets. We add a third regression to account for the nonlinearity by adding piecewise linear functions (see Glosten and Jagannathan (1994) and Diez De Los Rios and Garcia (2011)). Henceforth, we will denote the mimicking portfolios MP.

$$NLF_{j,t} = \beta_{0,j} + \beta'_{c,j} RC_t + \epsilon_{j,t} \quad t = 1, ..., T \tag{2.15}$$

$$NLF_{j,t} = \beta_{0,j} + \beta_{1,j} r_{mkt,t} + \beta'_{c,j} RC_t + \epsilon_{j,t} \quad t = 1, ..., T \tag{2.16}$$

$$NLF_{j,t} = \beta_{0,j} + \beta_{1,j} r_{mkt,t} + \beta'_{c,j} RC_t + \delta_j max(r_{mkt,t} - l_j, 0) + \epsilon_{j,t} \quad t = 1, ..., T \tag{2.17}$$

where the βs and δs are the regression coefficients, RC_t stands for the raw characteristics excess returns, $r_{mkt,t}$ for the market excess returns, l_j is the strike parameter of the call option j and $\epsilon_{j,t}$ for the error terms. The returns of the mimicking portfolios will be the predicted values of these regressions $MP = \hat{NLF}$. In the following section 2.4, we will present the basic case and we put the robustness checking analysis in the appendix B.4.

Let LF_{-k} be a set of $50 - k$ linear principal components, excluding the first k linear PCs and let $MP^{(k)}$ and $NLF^{(k)}$ be respectively a set of k mimicking portfolios from the third regression and nonlinear PCs. In the basic case, we price $[LF_{-k}, MP^{(k)}]$ using risk factors derived from $[LF_{-k}, MP^{(k)}]$. Namely, $\mu = \mathbb{E}([LF_{-k}, MP^{(k)}]), \Sigma = Cov([LF_{-k}, MP^{(k)}])$. To check the robustness of our results, we use directly the nonlinear principal components in the risk factors instead of their mimicking portfolios. Thereby, $\mu = \mathbb{E}([LF_{-k}, MP^{(k)}]), \Sigma = Cov([LF_{-k}, NLF^{(k)}])$

[7] See appendix for the computation details.

2.4 Findings

2.4.1 Fama-French 25 ME/BM-sorted portfolios

To acquire an intuition about the potential for capturing nonlinearities with the NLPC methodology, we start our analysis with the Fama-French 25 ME/BM-sorted portfolios. The properties of this set of test assets are well-known from previous studies, but most of the time in a linear factor-model context.[8] We consider five specifications for the stochastic discount factor and present the optimal model in Table B.2 in terms of out-of-sample R^2, Sharpe ratio of the mean-variance efficient portfolio, and scale parameter κ.

First, we estimate the SDF using all the 25 portfolio excess returns as factors (column 1). Second, we do the same exercise but using the 25 principal components extracted from the Fama-French 25 ME/BM-sorted portfolios as factors (column 2). Third, we estimate an hybrid model where we replace the first two linear principal components by two mimicking portfolios of the nonlinear factors extracted from the first two linear factors. This hybrid specification is reasonable because the nonlinearity dwell in the principal component with the highest variances or eigenvalues as mentioned before. Fourth, we estimate Fama-French 3-factor model, and finally we estimate the SDF using just 2-nonlinear factors. From the comparison of the performance of these specifications in Table B.2, we draw three main observations. Compared to the linear models, the nonlinear specifications lead to a higher out-of-sample R^2_{cv-oos}, a higher Sharpe ratio of the MVE portfolio, and a lower κ, which means that we impose more L2 shrinkage when we consider nonlinear factors.

2.4.2 Fifty Anomaly Portfolios

We now apply the same methodology to a set of fifty portfolios sorted according to different stock characteristics as in Kozak et al. (2020). We will proceed in a similar way as with the Fama-French 25 ME/BM-sorted portfolios by comparing linear specifications and parsimonious nonlinear specifications. We gather our results about the stochastic discount factor specifications in Figures B.5, B.6, B.7, and B.8. In the first two figures, we show the out-of-sample R^2's of a model using fifty raw characteristic excess returns (Figure B.5), and a model using fifty linear principal components (Figure B.6). We can see the difference between those two specifications as in Kozak et al. (2020). The left panel shows the R^2_{oos} in color map under the dual penalty. The right panel shows in red the R^2_{oos} pattern for different values of the tuning parameter or equivalently the Sharpe

[8] Ghosh et al. (2019) build a one-factor SDF from a large cross-section of equity portfolios based on entropy and show that it delivers smaller out-of-sample pricing errors and a better cross-sectional fit than leading factor models, in particular the three-factor Fama-French model that we consider in our analysis. The so-called information theoretic SDF is highly positively skewed and leptokurtic, and therefore captures nonlinearities in the test assets that imply compensation in the observed risk premia.

Ratio. From these graphs, we conclude that the projection of the SDF on the linear principal components space requires less factors to attain the maximum R^2_{oos} compared to the projection into the raw characteristics space, and that the difference between the two approaches in terms of the highest R^2_{oos} is small.

We now look at the projection of the stochastic discount factor into the hybrid space where we replace the first k linear factors ($k = 2$ for Figure B.7 and $k = 3$ for Figure B.8) by k mimicking portfolios of the nonlinear factors. In these graphs, we are pricing fifty factors (made of k mimicking portfolios and $50 - k$ linear factors. For both k values, we observe that we need fewer factors compared to the linear case in B.5 to reach the maximum R^2_{oos} under the elastic net penalty. With about 5 factors, the R^2_{oos} is now around 0.5. The LARS-EN algorithm adds the factors starting by the model with all the mimicking portfolios of the nonlinear factors. The mimicking portfolios are always kept among the selected factors in the optimal model. We can conclude that this captures more information than the linear factors that they replace since less factors are selected in the optimal model. In the right hand panels of Figures B.7 and B.8, which feature the R^2_{oos} under the ridge penalty ($\gamma_1 = 0$), we also report values higher than 50% compared to a bit more than 20% with the linear-factor analysis in Figure B.5.

2.4.3 Linear factors versus mimicking portfolios

We have put forward the importance of introducing nonlinearity in the stochastic discount factor estimation by replacing the linear factors with the highest variances by the mimicking portfolios of the nonlinear factors. As a matter of fact, the out-of-sample R^2 in average increases from 0.49 to 0.65 for the Fama-French 25 ME/BM-sorted portfolios data and from 0.22 to 0.55 for the fifty anomaly portfolios data. To better understand where this improvement comes from, we provide in Figures B.9 and B.10 a plot of the respective weights ($\frac{w_i}{\sum |w_i|}$) of the first two linear factors and the first two mimicking portfolios for the fifty anomalies and the twenty-five Fama-French portfolios. Let us first look at the characteristics portfolios. For the first factor, the main differences in exposures appear for idiosyncratic volatility, beta arbitrage, composite issuance, price and share volume. The weights for the other portfolios remain very similar between the linear and the mimicking portfolios. For the second factor, we observe differences for most factors, albeit with varied magnitudes. The large ones occur mainly for characteristics linked to momentum. The differences are much less apparent for the 25 FF portfolios, which is consistent with the fact that the portfolios are built with two characteristics, size and book-to-market, but we observe small differences for most of the portfolios for the first factor. There are relatively no significant differences between the linear and the mimicking portfolios for the second factor.

2.4.4 Interactions : Very high-dimensional data

In order to compare the nonlinearity introduced in this paper with the one of Kozak et al. (2020), we include in Figure B.11 the R^2_{oos} for the dual penalty both in the raw characteristics space and in the linear principal components space with the full set of 2600 portfolios of raw characteristics built by Kozak et al. (2020). It is important to emphasize that the optimal achievable R^2_{oos}s are not comparable with the results from our approach since we are not pricing the same assets. However, we can see in the right-hand panel that the optimal performance is obtained for a small number of PCs but that the maximum R^2_{oos} in the vicinity of 35%. It tells at least that our more parsimonious approach to construct nonlinear factors achieves a competitive performance.

2.5 Conclusion

This paper shows how truly independent nonlinear factors alongside linear principal components improve the prediction of future expected returns. We use the Fama-French 25 ME/BM-sorted portfolios and fifty anomaly portfolios built using individual stock characteristics to reveal the strengths of the truly independent nonlinear principal components. Then, we estimate the expected returns or equivalently the stochastic discount factor using risk factors derived from raw characteristic excess returns, linear principal component portfolio returns and nonlinear principal component (mimicking) portfolio returns. The hybrid model –using both nonlinear and linear principal components– requires less risk factors to achieve the highest out-of-sample performance compared to a model using only linear factors or a model projected into the raw characteristic returns. Plotting the weights of the anomalies on the linear principal component portfolios and the portfolios mimicking the nonlinear factors, we find a weight shifting on some anomalies. Our findings show that nonlinear principal components should be considered when the SDF is built with many anomalies since nonlinearities are likely to appear.

Chapter 3

Anomaly return predictability *

3.1 Introduction

The financial literature has put forward multiple anomalies (Harvey et al. (2016)). Those anomalies are firm characteristics or other observable variables that provide explanatory power for the cross-section of the sample mean returns beyond the beta of the CAPM or a benchmark factor model. To exploit these anomalies, researchers have proposed to sort the individual stock returns according to a given firm characteristic and build decile or quantile portfolios. The strategy consists in going long in the quantile with the highest returns and short in the one with the lowest returns, hoping to get the spread over a certain holding period. The chosen characteristics cover several categories such as Momentum, Value-versus-growth, Investment, Profitability, Intangibles, and Trading frictions. Many papers[1], the most prominent being McLean and Pontiff (2016), have tested the out-of-sample and post-publication performances of those anomaly portfolios. The general conclusion is that the out-of-sample or the post-publication performance of these anomaly strategies decays.

In this paper, we want to explore a different type of strategy based on the time series behavior of the quantile portfolios instead of the persistence of the cross-sectional return spread between extreme portfolios. We focus on the return dynamics of forty-eight anomaly portfolios chosen among the six above-mentioned categories. More specifically, we study the predictability of quantile portfolios of forty-eight well-known anomalies and propose a trading strategy that uses the predictability of the quantile portfolios. It will consist in going long in the quantile portfolio with the highest predicted return and shorting the quantile portfolio with the lowest predicted return.

To predict the decile-portfolio returns, we use three sets of information: past prices information, information about other variables (financial, macroeconomics, limit-to-arbitrage),

*I am indebted to my advisor, René Garcia for his invaluable guidance and support

[1] Jegadeesh and Titman (2001), Harvey et al. (2016), Green et al. (2017), Hou et al. (2020), Jacobs and Müller (2020), etc.

or a combination of both types of information. The choice of the best set of predictors is done according to two approaches. First, univariate predictive regressions are performed and I retain the set of predictors that has a good overall performance at predicting all decile portfolios. In the second approach, I use stepwise Akaike Information Criteria (AIC) regression, where the starting model uses all possible candidate predictors, and then the optimal model is chosen by adding and/or deleting predictor variables based on their AIC in a stepwise procedure until there is no predictor left to add or delete.

In addition to putting forward evidence of decile-portfolio predictability, we explore two investment strategies that differ from the usual strategies for all forty-eight anomaly variables. The first strategy consists of going long on the decile with the highest expected return and going short on the decile with the lowest expected return each month. The second strategy goes long on any decile for which the expected return exceeds a certain threshold and short on any decile for which the expected return is below a certain threshold.

We use monthly stock market data from the Center for Research in Security Prices (CRSP) and quarterly accounting data from Compustat to build decile portfolios. First, I construct forty-eight stock characteristics following the common definition of anomalies using different frequencies (month, quarter, year) depending on their definition. However, the values of the anomalies within each quarter or year are kept identical when the frequency of the anomaly is not monthly. Second, we drop penny stocks which contain all stocks for which the price is below five dollars. Third, for each month and each anomaly, stocks are sorted into deciles according to the anomaly value to build value-weighted returns of the firms in each decile (decile portfolios). Predictors come from Amit Goyal's website and are detailed in the Data section. We augment this set of predictors with the Chicago Fed activity index, the TED Spread, and the VIX CBOE volatility index. The final monthly data spans the period from January 1978 to December 2019 including 480 decile portfolios and sixteen predictors.

Our findings support the evidence of persistence in the decile and long-minus-short portfolios, suggesting that abnormal returns may find their source in risk-based and behavioral explanations. The predictive regressions reveal that the decile portfolio returns are predictable, especially by book-to-market, stock variance, dividend yield, dividend price ratio, long-term rate of return, corporate bond return, TED Spread, and VIX index. These findings extend Campbell and Shiller (1988) aggregate predictability results as dividend yield and dividend price ratio appear to be good predictors of the cross-section of returns. Moreover, a strategy consisting of going long on the decile with the highest expected return and short on the decile with the lowest expected return each month (hereafter called deciles-based strategy) produces much higher mean return and Sharpe ratio than the traditional long-short strategy based on the two extreme portfolios. For example, the deciles-based strategy delivers a monthly mean return of 1.30% (0.70%) for the size (value) anomaly and these means are statistically significant, while the traditional high-minus-low strategy corresponding means are 0.1% (0.1%) and are not significantly different from zero. This outperformance of the deciles-based strategy over the traditional strategy remains true for the other anomalies. The first four anomalies to stand out in decreasing order are Beta arbitrage (3.46% versus 0.1%), Idiosyncratic Volatility (2.57% versus 0.41%), Share Volume (2.39% versus 0.12%), and Momentum (2.30% versus 0.79%).

Returns' predictability is important for two main reasons. First, it helps to improve the performance of managed portfolios (DeMiguel et al. (2009), Haddad et al. (2020), etc.). Second, investors can benefit from returns' predictability by taking a long-term investment position (Barberis (2000), Detemple et al. (2003), etc.). Up to the 80s, the literature focused on the efficient market hypothesis (EMH)[2], interpreted as implying a constant equity premium or unpredictable excess stock returns.

The first evidence of stock returns' predictability–therefore of market inefficiency or time-varying expected returns– is shown by Shiller et al. (1981), Shiller et al. (1984), Summers (1986), and Fama and French (1988). Since then, the literature has found evidence of stock returns' predictability by using either past prices or other variables. Brock et al. (1992) find that twenty-six technical trading rules applied to the Dow Jones Industrial Average significantly outperformed a benchmark of buy and hold. Jegadeesh (1990), De Bondt and Thaler (1985), Jegadeesh and Titman (1993) show that short/intermediate/long-term past returns are related to future expected returns. Authors attribute this relation to microcaps, and data-snooping (see Sullivan et al. (1999), White (2000), etc.). White (2000) tested whether a given model has predictive superiority over a benchmark model after accounting for the effects of data-snooping. Campbell and Shiller (1988) use dividend yield to forecast future stock returns. Lamont (1998) uses dividend payout ratio to predict excess returns on both stocks and corporate bonds.

Though many papers support equity premium predictability, there are others that find evidence against it due to long-horizon regressions issues, small-sample biases, sampling issues (see Valkanov (2003), Lewellen (2004), Welch and Goyal (2008)). Haddad et al. (2020) studied the predictability of the first five principal components of fifty well-known anomaly returns using their own book-to-market ratio. They find strong evidence of predictability. They relied on this predictability to characterize the optimal factor timing portfolio and improve the estimation the stochastic discount factor (SDF). Arnott et al. (2016), Asness et al. (2000), Jacobs (2015), etc. use sentiment index, limits to arbitrage variables, and valuation ratios to forecast future anomaly returns. However, there are few studies from our knowledge (Cooper et al. (2002)) that looked at the predictability of anomaly quantiles' portfolio returns.

The paper is related to two additional strands of literature on the source of abnormal returns and the use of extreme quantiles to trade the anomalies. Abnormal returns are associated with three main sources: data mining, risk compensation (risk-based explanation), and limit-to-arbitrage or sentiment variables (behavioral explanation). If the

[2]The hypothesis states that all security prices fully reflect all available information. See Fama (1991).

abnormal return comes from data mining, it should not be persistent, however, if it comes from a risk-based or behavioral explanation then it can be persistent, and therefore predictable. Wang et al. (2021) and Cotter and McGeever (2018) studied the persistence of various anomalies produced by the literature. The former used limit-to-arbitrage variables to explain time-series momentum–constructed by going long the anomalies with positive past returns and short those with negative returns– and cross-sectional momentum–constructed based on two extreme quintiles: long the high past performance quintile and short the low past performance quintile– strategies returns such as arbitrage capital and illiquidity measures. They find that the profits of the momentum strategies are more pronounced when arbitrage capital is scarcer and market liquidity is lower. They also find that the persistence of long-short anomaly returns is short-lived and is not due to data mining. Concerning the latter, they found also that persistence is a matter of a short horizon. Therefore, this paper takes a simple autoregressive model AR(1) when using past prices to predict returns and uses an AR(1) term as a predictor in the multivariate predictive regression model. This paper differs from those papers because we analyze the persistence at the decile portfolio level and not only at the long-short portfolio level.

Several papers question the use of extreme quantiles to trade the anomalies. Papers here include Lai et al. (2022), and Cooper et al. (2002). Relying solely on the extreme deciles can provide surprising results and lower the potential return from a long minus short strategy. This paper is closely related to the one of Jacobs (2015) and Cooper et al. (2002). Jacobs (2015) studies the time-series dynamics of 100 anomalies using sentiment index and limit-to-arbitrage variables. Actually, they did not study those 100 anomalies individually but built 20 meta-anomalies by averaging long-short returns from the same anomaly groups. So, their study is at the aggregate level as opposed to this paper which looks at individual decile portfolios. We study the time-series dynamics of forty-eight anomalies at the deciles level using limit-to- arbitrage and macroeconomic variables as predictors. They found that the sentiment index explains well the dynamics of the meta-anomalies more than limit-to-arbitrage variables. However, the latter explain the dynamics of short-term reversal and deviations of the law of one price which is consistent with our findings. His findings about the others meta-anomalies are mitigated. Cooper et al. (2002) study book-to-market and size portfolios predictability as opposed to this paper which extends the set of anomalies considered. They constructed strategies going long and short in different deciles and found interesting results such as the outperformance of that strategy over the traditional which consists of going long and short in extreme deciles.

The remainder of the paper is organized as follows. Section 3.2 describes the data and methodology. Section 3.3 establishes the results. Section 3.4 concludes the paper.

3.2 Methodology and Data

This section describes the prediction models used in this paper, the data, and the trading strategies proposed to benefit from the predictability of the deciles' portfolios.

3.2.1 Methodology

Predictability

Three kinds of predictive regressions are proposed to analyze the predictability of the decile portfolios of forty-eight well-known anomalies:

$$\begin{aligned} Using\ past\ prices &: \quad r_{i,t+h} = \alpha_i + \rho_i r_{i,t+h-1} + \epsilon_{i,t+h} \quad (3.1) \\ Using\ other\ variables &: \quad r_{i,t+h} = \alpha_i + X'_{t+h}\beta_i + \epsilon_{i,t+h} \quad (3.2) \\ Combined\ regression &: \quad r_{i,t+h} = \alpha_i + \rho_i r_{i,t+h-1} + X'_{t+h}\beta_i + \epsilon_{i,t+h}, \quad (3.3) \end{aligned}$$

where the subscript i identifies the predicted assets (the decile portfolios), h denotes the prediction horizon ($h = 1$ for monthly prediction while $h = 12$ for annual prediction), X is a set of predictors (macroeconomic predictors, predictors related to stock characteristics, and limit-to-arbitrage predictors), and α_i, ρ_i and β_i are the regression coefficients. The AR(1) model allows to study the persistence of the returns of each decile as well as the long-short anomaly returns. The parameter ρ_i captures the degree of persistence of the return of portfolio i.

The forecasting literature has identified three approaches about the use of data to do out-of-sample forecasting analysis. The first approach is the recursive window regression consisting in using all information until the first split date and then expand the set of information for the next predictions (Fair and Shiller (1990), West (1996), Pesaran and Timmermann (1995), etc.). The second approach is the rolling window regression consisting in fixing the size of the regression window. So, as new information is added, oldest information is removed so that the window size is kept constant (Akgiray (1989),Giacomini and White (2006), etc.). The last approach is the fixed window regression consisting in fixing the size of the window, estimate the model once –as opposed to the rolling window regression– and predict all needed future information (Pagan and Schwert (1990), McCracken (2020), etc.). The prediction outputs may vary depending on the approach one adopt. The third approach is ruled out due to possible parameter instability when predicting stock returns as shown in the literature (see Pesaran and Timmermann (2002), Paye and Timmermann (2006), etc.). So, estimating the parameters once and keep them unchanged throughout the test sample is not an efficient way to assess the forecasting ability of the model. Therefore, we are left with either the rolling window regression or recursive window regression. West and McCracken (1998) proposed four regression-based tests – mean prediction error, efficiency, encompassing, and first-order serial correlation– that assess out-of-sample prediction errors of the three approaches listed above. Evidence

–about the size of nominal 0.05 tests– from that paper gives more support to the recursive window regression than the two others. Furthermore, the rolling window regression approach requires setting optimally or efficiently the length of the window –since the estimates depend on it– while the recursive method does not require setting the size of the window. Another advantage of the recursive method is its logical use of all available data and the estimates are less volatile. See Elliott and Timmermann (2016).

Hence, this paper adopts the recursive window regression to compute the OOS performance measures listed earlier by splitting the dataset into two: a training sample and a testing sample. The model is estimated over the first sample and uses the estimated coefficients to predict over the test sample, namely over the next month (for monthly prediction) or over the next twelve months (for annual prediction). Then, we add new information on the training sample and perform the same exercise. Let us consider the following model and December 1992 as the splitting date:

$$r_{i,t} = \alpha_i + \rho_i r_{i,t-1} + X_t' \beta_i + \epsilon_{i,t} \tag{3.4}$$

In that case, the equation 3.4 is estimated using information from January 1978 to December 1992. Then the estimated coefficients are used to predict the return of the corresponding asset in January 1993 for monthly prediction or predict the returns until December 1993 for annual prediction. Next, the information on January 1993 is added to the training sample and the equation 3.4 is re-estimated using information from January 1978 to January 1993. The corresponding coefficients are used to predict the return in February 1993. The same exercise is performed until the end of the sample– that is December 2019. In short:

$$For\ monthly\ prediction: \quad \hat{r}_{i,m+1} = \hat{\alpha}_i + \hat{\rho}_i r_{i,m} + X_m' \hat{\beta}_i \tag{3.5}$$

$$For\ annual\ prediction: \quad \hat{r}_{i,m+12} = \hat{\alpha}_i + \hat{\rho}_i r_{i,m+11} + X_{m+12}' \hat{\beta}_i \tag{3.6}$$

At the end of the procedure , we have the following series $\hat{r}_{i,m+1}$, $\hat{r}_{i,m+2}$, ..., $\hat{r}_{i,T}$ to compute out-of-sample (oos) R^2_{oos} and $MSPE_{oos}$ [3] for each portfolio using the equations below [4]:

$$R^2_{i,oos} = 1 - \frac{\sum_{t=m+1}^{T} (r_{i,t} - \hat{r}_{i,t})^2}{\sum_{t=m+1}^{T} (r_{i,t} - \bar{r})^2} \tag{3.7}$$

$$MSPE_{i,oos} = \frac{1}{T-m} \sum_{t=m+1}^{T} (r_{i,t} - \hat{r}_{i,t})^2 \tag{3.8}$$

[3] MSPE stands for Mean Squared Prediction Error

[4] Their in-sample versions are computed by estimating the models using the whole sample and computing all the predictions without re-estimating the models.
$R^2_{i,is} = 1 - \frac{\sum_{t=2}^{T} (r_{i,t} - \hat{r}_{i,t})^2}{\sum_{t=2}^{T} (r_{i,t} - \bar{r})^2}$ and $MSPE_{i,is} = \frac{1}{T-1} \sum_{t=2}^{T} (r_{i,t} - \hat{r}_{i,t})^2$

Where m is the length of the first training sample when computing the out-of-sample R^2s.

When performing predictive regressions, we are always interested in identifying the best set of variables that helps predict the response variable –in our case the returns. Previous literature has put forward two types of techniques to forecast the response when facing a large set of predictors: regularization and model/variable selection techniques. See in particular Tibshirani (1996), Hoerl and Kennard (1970), Zou and Hastie (2005), for regularization techniques, and James et al. (2013), Heinze et al. (2018), Yu et al. (2007), for model/variable selection techniques. More specifically, Brownlees and Gallo (2008) use the variable selection method to predict the realized volatility and the value at risk (VaR). They find that using variable selection, the VaR forecasts improved significantly. Aït-Sahalia and Brandt (2001) show that variable selection helps investors to select the predictors or the set of predictors to use in their portfolio formation. Moreover, investors do not know a priori which economic or financial variables will predict well the returns. So, the variable selection technique is one of their best options to predict future returns by using all predictors the literature has pointed out as potential predictors.

Therefore, the choice of the best set of predictors– that is X in equation 3.4–is done in this paper using two approaches. In the first approach, univariate predictive regressions are performed and we retain the set of predictors that have a good overall performance[5] at predicting all decile portfolios. In the second approach, stepwise Akaike Information Criteria (AIC) regression[6] –a model selection technique– is used. In this approach, the starting model uses all potential candidate predictors based on all information sources, and then the optimal model is chosen by adding and/or deleting predictor variables based on their AIC in a stepwise procedure until there is no predictor left to add or delete. Basically, the two approaches are different because the first uses the same set of predictors for all decile portfolios over all the training samples. But the second approach may use a different set of predictors from one decile portfolio to another and from a training sample to another. The use of different predictive models helps to determine the robustness of deciles-based strategies.

Trading strategies

The usual trading strategy when it comes to benefiting from the mispricing brought by the anomalies is to go long and short the extreme quantiles. An example of such a traditional trading rule is the SMB or HML type of strategy (see Fama and French (1993)). Most papers in the literature have adopted this rule to assess the profitability of the anomalies. This paper departs from this literature and proposes trading strategies similar to Cooper et al. (2002). The purpose of these strategies is to benefit from the

[5] We measure the overall performance by the out-of-sample R^2s

[6] We use AIC instead of BIC because of the end goal which is the prediction. See Stone (1977), Shmueli (2010)

cross-decile returns' variation. The mean returns vary a lot within the deciles (see Table C.1 for more details), and any investor should be willing to build an investment strategy based on this observation. For each of the forty-eight anomaly variables, we propose two types of strategy. The first one consists of going long on the decile with the highest expected return and short on the decile with the lowest expected return each month. The second strategy consists of going long any decile for which the expected return exceeds a certain positive threshold and going short on any decile for which the expected return is below a certain negative threshold. If there are no decile portfolios above or below the thresholds, the strategy suggests going long/short on the 1-month T-bill. This second strategy is similar in spirit to filter rules (see Fama and Blume (1966), Sweeney (1988), etc.). We use the level of the expected returns and the threshold to filter decile portfolios at each period. We buy and hold deciles that have high expected returns while selling deciles that have low expected returns. The idea behind this strategy is to take effective long and short positions. An effective long (short) position means go long (short) on deciles with positive (negative) expected returns in order to have a positive profit. The threshold can be determined arbitrarily (as in Cooper et al. (2002)) based on the investor risk appetite or preference. We propose to set the threshold at the average level of the risk-free rate. One can choose optimally the threshold by minimizing a criteria –for example the transaction cost– or by maximizing a criteria –for example the terminal wealth, the average profit, etc. The expected returns are obtained using the predictive regressions proposed in this paper. The performance of the proposed strategies is assessed by using the mean return, Sharpe ratio, and the terminal wealth generated by the strategy compared to the one generated by the traditional trading rule.

In addition, we assess the after-trading-cost performance of our strategies using the framework of Farouh and Garcia (2021) to estimate trading costs. We want to make sure that all of the profits generated by the proposed strategies are not erased by the transaction costs. Their transaction costs estimation model can be summarized into one equation:

$$\Delta p_t^i = c_{0,t_p}^i \times \Delta q_t^i + c_{1,t_p}^i \times FR_t \times \Delta q_t^i + \beta_m^i r_{m,t} + \epsilon_t^i \tag{3.9}$$

where p_t^i stands for the log trade price, q_t^i is a variable specifying the trade direction. $q_t^i = 1$ if it took place at the ask and $q_t^i = -1$ if it took place at the bid. $r_{m,t}$ is the market return, FR_t is the financial risk, $\epsilon_t^i \overset{iid}{\sim} \mathcal{N}(0, \sigma_{\epsilon_i}^2)$[7] is the error term. The time subscript t (t_p) denotes the daily frequency (the time period over which the trading cost are estimated, either monthly or annually). The wanted trading cost is $c_t^i = c_{0,t_p}^i + c_{1,t_p}^i \times FR_t$. All the parameters are estimated using a Bayesian approach (see Hasbrouck (2009), and Farouh and Garcia (2021)). In our strategy, we can go long or short any decile. So, all the deciles have a chance to be selected. We compute the frequency of inclusion of each decile for each anomaly analyzed. The frequency of inclusion of a decile

[7] Normal distribution

j is the number of time we take a –long or short– position in this decile. This helps us to compute the weighted average transaction cost serving to calculate the after-trading-cost performance of the strategies. The weighted average transaction costs of the long, and short positions are calculated using the following equation:

$$tcost^i_{d,p} = \sum_{j=1}^{10} freq^i_{j,p} \times tcost^i_j \tag{3.10}$$

$$tcost^i_{b,p} = tcost^i_1 \quad \text{or} \quad tcost^i_{10} \tag{3.11}$$

where $tcost^i_{d,p}$ ($tcost^i_{b,p}$) is the weighted average transaction cost of the position p=long or short using the deciles-based (benchmark) strategy for anomaly i, d stands for deciles-based strategy, b for benchmark strategy, $p = L, S$ for long and short, $freq^i_{j,p}$ denotes the frequency of inclusion of decile j in the position p for anomaly i, and $tcost^i_j$ is the annualized average transaction cost of trading j^{th} decile of anomaly i. Finally, we compute the after-trading-cost return by taking the difference between the annualized gross return of the long-short strategy $s = d$ or b and the corresponding transaction cost as it follows:

$$netR^a_{s,i} = R^a_{s,i} - tcost^i_{s,L} - tcost^i_{s,S} \tag{3.12}$$

where $R^a_{s,i}$ is the annualized gross return, $netR^a_{s,i}$ is the net of transaction cost return, a stands for annualized, i for anomaly, s for strategy.

3.2.2 Data

This paper builds the dependent variables using monthly stock market data from the Center for Research in Security Prices (CRSP) and quarterly accounting data from Compustat. First, we construct forty-eight stock characteristics following the common definition of anomalies (Novy-Marx and Velikov (2016), Kozak et al. (2020)). The full list of the anomalies used in this paper is provided in Table B.1 and their definitions in the section B.3 of the Appendix. Anomalies are constructed using different frequencies (month, quarter, year) depending on their definition. However, the values of the anomalies within each quarter or year are kept identical when the frequency of the anomaly is not monthly. Second, we drop penny stocks which contain all stocks for which the price is below five dollars. Third, for each month and each anomaly, we sort the stocks into deciles according to the anomaly value to build deciles' portfolios. Finally, the dependent variables are computed as the value-weighted returns of the firms in each decile.

Predictors are those used by Welch and Goyal (2008) augmented by the Chicago Fed activity index and two limit-to-arbitrage predictors: book-to-market (b.m), Treasury bills (tbl), long-term yield (lty), net equity expansion (ntis), inflation (infl), long-term rate of return (ltr), corporate bond return (corpr), stock variance (svar), Dividend price ratio (Dpr), Dividend yield (Dy), Earning price ratio (Epr), Dividend Payout Ratio (Der), Default yield spread (Dfy), Chicago Fed National Activity Index (gro_p), TED spread (Garleanu and Pedersen (2011)) and Amihud Illiquidity measure (Amihud (2002)).

The final monthly data span the period from January 1978 to December 2019 including 480 decile portfolios and sixteen predictors.

3.3 Findings

Our predictive models use three information sets : past prices, set of macroeconomic, financial and limit-to-arbitrage variables, or a combination of the two types of information. We present the respective findings obtained with these three different sets of predictors. We also report the performance of the trading strategies described above.

3.3.1 Predictability of the decile portfolios

Using only past prices

The prediction analysis using only past prices (see Appendix C.9) reveals that some decile portfolios are predictable at monthly horizon because their associated out-of-sample R^2_{oos} are positive. This is in line with papers showing that persistence is a short-term phenomenon (see Wang et al. (2021) and Cotter and McGeever (2018)). These decile portfolios are consistently predictable because the methodology does not depend on the choice of a split date. Most of the predictable decile portfolios remain predictable after the change of the split date.

Using financial, macroeconomic and limit-to-arbitrage variables

The following results correspond to 1992m12 as a split date– which means that the forecasting starts as of 1993m1 when using only other variables and starts as of 1993m2 when using also past prices. A robustness check is performed with respect to a change in the split date by choosing 2004m12 following Stock and Watson (2006) and Inoue and Kilian (2008) . They suggest choosing the split date such that one has enough data to estimate and enough range to do the out-of-sample exercise. In addition, Rapach et al. (2010) and Welch and Goyal (2008) suggest considering multiple split dates. The robustness check analysis reveals similar results as those presented in this section.

As mentioned in section 3.2.1, the first prediction approach consists of running univariate regressions and keeping predictors that have good performance at predicting all the 480 decile portfolios. The results of the univariate regressions can be found in Table C.10. Overall, six predictors have good predictive power at monthly horizon and predict consistently almost all the deciles using a univariate regression model: book-to-market, stock variance, dividend yield, dividend-price ratio–stock characteristic variables– and long-term rate of return, corporate bond return–interest rate related variables. Therefore, we run a predictive regression using these six predictors–columns 2 and 7 (model 1) of Table C.2 –for all the decile portfolios. Columns 3, 6, and 8 of Table C.2 are variations of model 1 where some predictors are added –either AR(1) term or limit-to-arbitrage variable (VIX and TED Spread) or both.

Let us take model 1 and look at the predictability of the decile portfolios of the two well-known anomalies (size, and value). The returns of their deciles are predictable and the degree of predictability varies across deciles and anomalies. For example, the first five most predictable deciles of the size anomaly in decreasing order of their R^2_{oos} are the second, third, tenth, fourth, and the fifth. While the first five most predictable deciles of the value anomaly are the tenth, eighth, seventh, fourth, and sixth. The R^2_{oos} asssociated with the value anomaly deciles ranges from 3.6% to 19.6%, while for the size it varies between 11.4% and 17.4%, showing less volatility. The last decile is the least predictable for six anomalies (prof, aturnover, indmom, roa, betaarb, shvol) and the extreme deciles tend to be among the least predictable (lowest R^2_{oos}) for many anomalies (lev, roaa, sp among others.). The R^2_{oos} drastically increases when we add the past prices information as predictors (model 2). That observation confirms the findings in section 3.3.1 showing the persistence property of the decile returns. The pattern in R^2_{oos} is still the same as in model 1. Thus, investors should not look only at the extreme deciles when forming investment strategies even though they are among the most predictable for some anomalies.

Among the six strong predictors identified in the univariate predictive regressions, some of them may be good predictors for specific deciles of certain characteristic portfolios. For example, predictors such as dividend yield or dividend-price ratio share some common information with the decile portfolios to be predicted such as earning-price ratio or dividend yield (as in Lamont (1998), and Campbell and Shiller (1988)). Therefore, we perform stepwise regressions (model selection analysis) to allow the model to select the best set of predictors for each decile portfolio. The findings for these predictive regressions where the set of predictors may change from one decile to another are presented in columns 4 and 9 of Table C.2 (Model 3). We find that most of the previous six well-performing predictors from the univariate regressions are retained when performing the variable selection technique albeit the R^2_{oos}s from Model 3 are smaller than the ones from Model 1. Once again, we observe the same pattern in the R^2_{oos}s. Extreme deciles of some anomalies are still among the least predictable. The R^2_{oos} of the size (value) anomaly ranges from 3.6% to 13.4% (-2.2% to 14.9%) less (more) volatile. For this model, the last three deciles of share volume (shvol) and industry momentum (indmom) anomalies are not predictable at all. They have negative R^2_{oos}s. So, it suggests that we cannot rely on these extreme deciles to form a trading strategy as put forward in the literature. The findings and interpretations do not change that much when we change the split date. We still find the same pattern in the R^2_{oos}s.

Overall, all the deciles are predictable by the selected set of predictors used in Model 1 and Model 2 because they deliver positive R^2_{oos} for all the portfolios. Therefore, we find support of return predictability using past information (prices and other variables) as shown in some papers after the 80s (Haddad et al. (2020), Arnott et al. (2016), Cooper et al. (2002), Jegadeesh and Titman (1993), among others). The other models give pretty good results too–with some exceptional negative R^2_{oos} for a few specific deciles. The preferred model by far is Model 2– Model 1+ AR(1) term– that includes the persistence property of deciles found in section 3.3.1. The decile portfolios of some anomalies are monotonically predictable– decreasing R^2 or U-shape.

Overall, the decile portfolios are predictable and this predictability can be used to build an investment strategy. Besides, extreme deciles are not necessary more predictable than the middle deciles. Consequently, a strategy investing in any of the deciles based on their expected returns – deciles-based strategy– is proposed, analyzed, and compared to the usual benchmark trading strategy consisting of investing only in the extreme deciles (see section 3.3.2).

3.3.2 Trading strategies

In this section, we introduce a portfolio analysis in order to exploit the predictability found in section 3.3.1. Results are displayed in Table C.3. A first glance at the table shows clearly that the deciles-based strategy outperforms the benchmark strategy.

First, the mean returns (column μ_m) of the long minus short portfolios of the deciles-based strategy are positive and significant at 5% except for two anomalies– Asset Turnover and Standardized Unexpected Earning, while only 11 out of 48 are significant if we long (short) the first decile and short (long) the tenth decile. Even when the mean return of the benchmark long-minus-short strategy is positive, it is lower than the mean return of the deciles-based strategy. The t-statistic test shows that both mean returns are significantly different (see the last column of the table). The top five anomalies for which our deciles-based strategy yields a monthly return above 2% are betaarb (3.5%), ivol (2.6%), shvol (2.4%), mom12 (2.3%), and rome (2%). In contrast, none of the 11 significantly positive returns produced by the benchmark strategy is above 1%. The highest is 0.9% for the market equity (rome) anomaly.

Second, the terminal wealth of investing 1$ at the beginning of the forecasting period (column tw) and reinvesting the proceeds over the sample period is always greater for the deciles-based strategy. The terminal wealth is large enough for the previous top five anomalies –betaarb (38,330$), ivol (2027$), shvol (1365$), mom12 (728$), rome (422$) to potentially offset the transaction cost. Moreover, the breakeven transaction cost incurred to equate the long position mean returns of both trading rules for each anomaly is reasonable (breakeven t-cost column of Table C.3).

Tables C.4 and C.5 give detailed information about the frequency with which each decile is selected in the long and short strategies respectively. It is clear that all deciles are selected at one point or another for all anomalies, implying that the deciles-based strategy dominates the benchmark one. Depending on the anomaly, we do select more often some deciles than others.

Let us look at the deciles-based strategy applied to size and value anomalies compared to the traditional HML and SMB. The HML type strategy takes a long position 100% of the time in the high book-to-market (value anomaly) stocks–the last decile– while the proposed deciles-based strategy takes a long position of 41% of the time in the last decile, 17% of the time in the eighth decile, 15% of the time in the first decile. For the short side, it takes a short position 100% of the time in the low book-to-market stocks–the first decile, while the proposed deciles-based strategy takes a short position 40% of the time in the first decile, 28% of the time in the ninth decile, and 9% of the time in the eighth decile.

Regarding the SMB type strategy, it takes a long position of 100% of time in the small market capitalization (size anomaly) stocks–the first decile– while the proposed deciles-based strategy takes a long position of 38% of the time in the last decile, 19% of the time in the ninth decile, 19% of the time in the first decile. It takes a short position 100% of the time in the big market capitalization stocks–the last decile– while the proposed deciles-based strategy takes a short position 45% of the time in the first decile, 10% of the time in the ninth decile, 22% of the time in the tenth decile. Giving the flexibility to take a long-short position in any decile increases considerably the mean return of the long minus short portfolio. A deciles-based strategy delivers a mean return of 1.30% (0.70%) for the size (value) anomaly and these means are significant. Meanwhile, the usual HML (SMB) type strategy delivers 0.1% (0.1%) for the value (size) anomaly and they are not even significant.

In addition, Figure C.1 plots the time-series of the top four mean returns of the long-minus-short deciles-based strategies with the corresponding returns of the benchamark strategy. It includes, in decreasing order, Beta arbitrage (Betaarb), Idiosyncratic Volatility (Ivol), Share Volume (Shvol), and Momentum (Mom12) anomalies. During and after times of crisis, such as the Financial crisis in 2008, our strategy is able to generate positive profit. The profit generated by the benchmark strategy investing in betaarb, ivol, and mom12 anomalies starts dropping around 2009 and reach a trough around 2010 while our strategy was able to generate increasing profit around 2009 and reach a peak around 2010. These results hold as well for the dot-com bubble in the late 1990s.

We also plot the corresponding cumulative returns of the four pairs of strategies (see Figure C.2). The deciles-based strategy outperformed the traditional one based on the unadjusted profit measure (see Table C.3 and C.7) and the risk-adjusted measure (see Table C.6 for the Sharpe Ratio comparison). The Sharpe Ratios are not excessively high, contrary to the suggestion by Haddad et al. (2020), and are positive. Eighteen out of forty-eight anomalies have a good Sharpe Ratio (SR above 1). The top five anomalies for which our deciles-based strategy delivers a good SR are betaarb (2.22), shvol (1.6), indrrev (1.6), ivol (1.4), and rome (1.3). The risk-adjusted returns (SRs) for the benchmark strategy are less than 1.

The mean returns of our long-short strategy are much higher when considering the expected returns filter rule (see Table C.7). The reason is that we only take effective long (returns always positive) and short (returns always negative) positions. The monthly average returns are all above 3% and less volatile. It goes from 2.96% to 3.94%. Moreover, the Sharpe Ratios of this expected return filter rule are near or above 1. It goes from 0.94 to 1.20. However, the transaction cost may be higher compared to the strategy that goes long (short) the decile with the highest (lowest) expected returns. The explanation of this potential high transaction cost lies in the number of deciles to go long or short. In fact, the expected returns filter rule can go long-short many deciles as long as they pass the filtering rule, while the other deciles-based strategy goes long-short one decile at a time. Can the profits generated by our strategies survive after considering the transaction costs? We will discuss this matter in the next section.

3.3.3 Transaction costs

In the proposed strategies, we can change the deciles we invest in each month (rebalancing) and that is a source of transaction costs incurred by the investors. We discuss this issue in this section and propose a way to minimize the transaction cost. Previous literature has put forward transaction cost mitigation methods. Novy-Marx and Velikov (2016) propose three ways to reduce transaction costs. First, one can reduce the trading cost by reducing the strategy rebalancing frequency. Second, one can reduce the trading cost by trading only cheap-to-trade stocks. Third, they suggest introducing a buy/hold spread that discourages investors to enter into a position. They show that the most effective way to reduce transaction costs is the latter.

Before analyzing the method that might effectively reduce the transaction cost in our proposed strategies, let us analyze the situation. In an ideal world where the transaction cost is reasonable (low), we show that our proposed strategies beat the traditional long-short strategy based on extreme deciles and that the breakeven transaction costs that equate the mean return of our strategy to the mean return of the traditional strategy are low (see the breakeven t-cost column in Table C.3). Of the two strategies we proposed, the expected returns filter rule is the one that will generate high transaction costs. Therefore, we compute after-trading-cost returns for the strategy that goes long the decile with the highest expected return and goes short the decile with the lowest expected return (see Table C.8). Next, we suggest a mitigation method for the filtering rule strategy.

Looking at Table C.8, we can see that the weighted average transaction costs of our strategy are lower than the transaction cost of the benchmark strategy calculated using equations 3.11 and 3.10. Transaction costs (annualized) of the deciles-based strategy go from 1.5% to 4.5% while the transaction costs (annualized) for the benchmark strategy range from 1.6% to 5%. The cheapest anomalies to trade are the return on market equity (1.5%) and leverage (2.5%) for our strategy and return on market equity (1.6%) and growth in long-term net operating assets (2.6%) for the benchmark strategy. Among the anomalies for which our strategy generates significant profit (see Table C.3), all of their after-transaction-cost returns (annualized) are positive. On the opposite, inv, accruals, and aturnover do not generate a positive net profit for the benchmark strategy. Moreover, the net profit of our strategy is far above the benchmark's net profit.

In a world where the transaction cost is important, we can still find a strategy that beat the traditional long-short strategy by applying the expected return filter rules. A solution is to set the threshold at a high value and then reduce the number of active trading months, months where there is at least one decile that passes the filter. Hence, successfully reducing the number of active trading months (less rebalancing) leads to low transaction costs. This is in line with one of the solutions proposed by Novy-Marx and Velikov (2016) –which consists in reducing strategy rebalancing frequency. Another solution will be to reduce the set of deciles for which we can potentially take a position to the cheapest-to-trade deciles. An optimal solution will be to find the optimal threshold –defined as the threshold that minimizes the transaction cost. It will consist in applying the expected returns filter rule for many values of the threshold and taking the value that minimizes the transaction cost.

3.4 Conclusion

This paper studies anomaly return predictability across deciles using a set of forty-eight anomaly variables built using individual stock characteristics. After constructing the decile portfolios, this paper studies their predictability using past prices, and other well-known predictors. The analyses reveal that some decile portfolio returns are persistent. In addition, decile portfolio returns are predictable by book-to-market, stock variance, dividend yield, dividend price ratio, long-term rate of return, corporate bond returns, the TED Spread, and the VIX index. Moreover, a strategy consisting of going long on the decile with the highest expected return and short on the decile with the lowest expected return each month gives a way better mean returns and Sharpe ratio than the traditional strategy for forty-five out of forty-eight anomalies. The deciles-based strategy delivers a monthly mean return of 1.30% (0.70%) for the size (value) anomaly and these means are significant. Meanwhile, the usual HML (SMB) type strategy delivers 0.1% (0.1%) for the value (size) anomaly and they are not significant. This outperformance of the deciles-based strategy over the traditional strategy remains true for the other anomalies. The first four anomalies to stand out in decreasing order are Beta arbitrage (3.46% versus 0.1%), Idiosyncratic Volatility (2.57% versus 0.41%), Share Volume (2.39% versus 0.12%), and Momentum (2.30% versus 0.79%). While tansaction costs reduce profits, deciles-based strategies still appear to generate a positive performance but a more thorough analysis needs to be performed.

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Appendix A

Appendix to Chapter 1

A.1 Consumption growth decomposition

Let us consider I categories of consumption among which J carbon consumption categories and $I - J$ green consumption categories.

$$C_t = \sum_{i=1}^{I} C_{i,t} \tag{A.1}$$

$$C_t = \sum_{i=1}^{J} C_{i,t} + \sum_{i=J+1}^{I} C_{i,t} \tag{A.2}$$

$$C_t = CC_t + GC_t \tag{A.3}$$

Growth rate decomposition :

$$\Delta c_{t+1} = \log(CC_{t+1} + GC_{t+1}) - \log(CC_t + GC_t) \tag{A.4}$$

$$\Delta c_{t+1} = \log(CC_{t+1}) + \log \frac{CC_{t+1} + GC_{t+1}}{CC_{t+1}} - \log(CC_t) - \log \frac{CC_t + GC_t}{CC_t} \tag{A.5}$$

$$\Delta c_{t+1} = \Delta cc_{t+1} - \left(\log \frac{CC_{t+1}}{CC_{t+1} + GC_{t+1}} - \log \frac{CC_t}{CC_t + GC_t} \right) \tag{A.6}$$

$$\Delta c_{t+1} = \Delta cc_{t+1} - \Delta \alpha_{CC,t+1} \tag{A.7}$$

$$Or \;\; \Delta c_{t+1} = \Delta cc_{t+1} - \Delta \alpha_{gc,t+1} + \Delta \chi_{gc,cc,t+1} \tag{A.8}$$

where Δc_{t+1}, Δcc_{t+1} and $\Delta \alpha_{CC,t+1}$ are consumption, carbon consumption and carbon consumption share growth rates (log-difference) respectively, and $\chi_{gc,cc,t} = \log \frac{GC_t}{CC_t}$

A.2 Price of risks

$$\lambda_{m,\alpha} = (-\gamma + (1-\theta)\kappa_1 A_3) \tag{A.9}$$

$$\lambda_{m,cc} = \gamma + (-\gamma + (1-\theta)\kappa_1 A_3)\,\pi \tag{A.10}$$

$$\lambda_{m,x} = (1-\theta)\kappa_1 A_1 \psi_x \tag{A.11}$$

$$\lambda_{m,w} = (1-\theta)\kappa_1 A_2 \tag{A.12}$$

are prices of risk that correspond to the four sources of risk $\epsilon_{\alpha,t+1},\ \epsilon_{cc,t+1},\ \epsilon_{x,t+1}, \epsilon_{\sigma,t+1}$.

A.3 Theoretical moments calculation

From the carbon/green consumption growth rate processes, we have :

$$\mathbb{E}[\Delta cc_{t+1}] = \nu_{cc} \tag{A.13}$$

$$\mathbb{E}[\Delta \alpha_{cc,t+1}] = \nu_{\alpha} \tag{A.14}$$

$$\begin{aligned}\mathbb{V}[\Delta cc_{t+1}] &= \mathbb{V}[\nu_{cc} + x_t + \sigma_t \epsilon_{cc,t+1}] \\ &= \mathbb{V}[x_t] + \mathbb{V}[\sigma_t \epsilon_{cc,t+1}] \\ &= \frac{\psi_x^2}{1-\rho_x^2}\sigma^2 + \sigma^2 \end{aligned} \tag{A.15}$$

$$\begin{aligned}\mathbb{V}[\Delta\alpha_{cc,t+1}] &= \mathbb{V}[\nu_\alpha(1-\rho_\alpha) + \rho_\alpha \Delta\alpha_{cc,t} + \sigma_\alpha \epsilon_{\alpha,t+1} + \pi\sigma_t\epsilon_{cc,t+1}] \\ (1-\rho_\alpha^2)\mathbb{V}[\Delta\alpha_{cc,t+1}] &= \sigma_\alpha^2 + \pi^2\sigma^2 \\ \mathbb{V}[\Delta\alpha_{cc,t+1}] &= \frac{\sigma_\alpha^2 + \pi^2\sigma^2}{1-\rho_\alpha^2} \end{aligned} \tag{A.16}$$

$$Cov[\Delta cc_{t+1}, \Delta cc_{t+2}] = \rho_x \frac{\psi_x^2}{1-\rho_x^2}\sigma^2 \tag{A.17}$$

$$\begin{aligned}Cov[\Delta\alpha_{cc,t+1}, \Delta\alpha_{cc,t+2}] &= Cov[\Delta\alpha_{cc,t+1}, \rho_\alpha\Delta\alpha_{cc,t+1} + \sigma_\alpha\epsilon_{\alpha,t+2} + \pi\sigma_{t+1}\epsilon_{cc,t+2}] \\ &= \rho_\alpha \mathbb{V}[\Delta\alpha_{cc,t+1}] \\ &= \rho_\alpha \frac{\sigma_\alpha^2 + \pi^2\sigma^2}{1-\rho_\alpha^2} \end{aligned} \tag{A.18}$$

From the dividend growth rate process, we can get :

$$\mathbb{E}[\Delta d_{t+1}] = \nu_i + \phi_{\alpha,i}\nu_\alpha \tag{A.19}$$

$$\begin{aligned}\mathbb{V}[\Delta d_{i,t+1}] &= \phi_i^2 \mathbb{V}[x_t] + \phi_{\alpha,i}^2 \mathbb{V}[\Delta\alpha_{cc,t}] + \psi_i^2 \mathbb{V}[\sigma_t\epsilon_{i,t+1}] \\ &= \phi_i^2 \frac{\psi_x^2}{1-\rho_x^2}\sigma^2 + \phi_{\alpha,i}^2 \frac{\sigma_\alpha^2 + \pi^2\sigma^2}{1-\rho_\alpha^2} + \psi_i^2\sigma^2 \end{aligned} \tag{A.20}$$

$$
\begin{aligned}
Cov[\Delta d_{i,t+1}, \Delta d_{i,t+2}] &= Cov[\phi_i x_t + \phi_{\alpha,i}\Delta\alpha_{cc,t} + \psi_i \sigma_t \epsilon_{i,t+1}, \phi_i x_{t+1} + \phi_{\alpha,i}\Delta\alpha_{cc,t+1} + \psi_i \sigma_{t+1}\epsilon_{i,t+2}] \\
&= \phi_i^2 Cov[x_t, x_{t+1}] + \phi_{\alpha,i}^2 Cov[\Delta\alpha_{cc,t}, \Delta\alpha_{cc,t+1}] \\
&= \phi_i^2 \rho_x \mathbb{V}[x_t] + \phi_{\alpha,i}^2 \rho_\alpha \frac{\sigma_\alpha^2 + \pi^2\sigma^2}{1-\rho_\alpha^2} \\
&= \phi_i^2 \rho_x \frac{\psi_x^2}{1-\rho_x^2}\sigma^2 + \phi_{\alpha,i}^2 \rho_\alpha \frac{\sigma_\alpha^2 + \pi^2\sigma^2}{1-\rho_\alpha^2} \qquad \text{(A.21)}
\end{aligned}
$$

From both carbon/green consumption and dividend growth rates, we get the cross moments :

$$
\begin{aligned}
Cov[\Delta\alpha_{cc,t+1}, \Delta cc_{t+1}] &= Cov[\rho_\alpha \Delta\alpha_{cc,t} + \sigma_\alpha \epsilon_{\alpha,t+1} + \pi\sigma_t \epsilon_{cc,t+1}, x_t + \sigma_t \epsilon_{cc,t+1}] \\
&= \pi \mathbb{V}[\sigma_t \epsilon_{cc,t+1}] \\
&= \pi\sigma^2 \qquad \text{(A.22)}
\end{aligned}
$$

$$
\begin{aligned}
Cov[\Delta d_{i,t+1}, \Delta cc_{t+1}] &= Cov[\phi_i x_t + \phi_{\alpha,i}\Delta\alpha_{cc,t} + \psi_i \sigma_t \epsilon_{i,t+1}, x_t + \sigma_t \epsilon_{cc,t+1}] \\
&= \phi_i \mathbb{V}[x_t] \\
&= \phi_i \frac{\psi_x^2}{1-\rho_x^2}\sigma^2 \qquad \text{(A.23)}
\end{aligned}
$$

$$
\begin{aligned}
Cov[\Delta d_{i,t+1}, \Delta\alpha_{cc,t+1}] &= Cov[\phi_i x_t + \phi_{\alpha,i}\Delta\alpha_{cc,t} + \psi_i \sigma_t \epsilon_{i,t+1}, \rho_\alpha \Delta\alpha_{cc,t} + \sigma_\alpha \epsilon_{\alpha,t+1} + \pi\sigma_t \epsilon_{cc,t+1}] \\
&= \phi_{\alpha,i}\rho_\alpha \mathbb{V}[\Delta\alpha_{cc,t}] \\
&= \phi_{\alpha,i}\rho_\alpha \frac{\sigma_\alpha^2 + \pi^2\sigma^2}{1-\rho_\alpha^2} \qquad \text{(A.24)}
\end{aligned}
$$

From the log price dividend process:

$$
\mathbb{E}[z_{i,t}] = A_{0,i} + A_{2,i}\sigma^2 + A_{3,i}\nu_\alpha \qquad \text{(A.25)}
$$

$$
\mathbb{V}[z_{i,t}] = A_{1,i}^2 \frac{\psi_x^2}{1-\rho_x^2}\sigma^2 + A_{2,i}^2 \frac{\sigma_w^2}{1-\nu^2} + A_{3,i}^2 \frac{\sigma_\alpha^2 + \pi^2\sigma^2}{1-\rho_\alpha^2} \qquad \text{(A.26)}
$$

$$
\begin{aligned}
Cov[\Delta d_{i,t+1}, z_{i,t}] &= Cov[\phi_i x_t + \phi_{\alpha,i}\Delta\alpha_{cc,t} + \psi_i \sigma_t \epsilon_{i,t+1}, A_{1,i}x_t + A_{2,i}\sigma_t^2 + A_{3,i}\Delta\alpha_{cc,t}] \\
&= \phi_i A_{1,i} \frac{\psi_x^2}{1-\rho_x^2}\sigma^2 + \phi_{\alpha,i} A_{3,i} \frac{\sigma_\alpha^2 + \pi^2\sigma^2}{1-\rho_\alpha^2} \qquad \text{(A.27)}
\end{aligned}
$$

$$
\begin{aligned}
Cov[\Delta c_{t+1}, z_{i,t}] &= Cov[\Delta cc_{t+1} - \Delta\alpha_{cc,t+1}, A_{1,i}x_t + A_{2,i}\sigma_t^2 + A_{3,i}\Delta\alpha_{cc,t}] \\
&= Cov[x_t + \sigma_t \epsilon_{cc,t+1}, A_{1,i}x_t + A_{2,i}\sigma_t^2 + A_{3,i}\Delta\alpha_{cc,t}] \\
&- Cov[\rho_\alpha \Delta\alpha_{cc,t} + \sigma_\alpha \epsilon_{\alpha,t+1} + \pi\sigma_t \epsilon_{cc,t+1}, A_{1,i}x_t + A_{2,i}\sigma_t^2 + A_{3,i}\Delta\alpha_{cc,t}] \\
&= A_{1,i} \frac{\psi_x^2}{1-\rho_x^2}\sigma^2 - \rho_\alpha A_{3,i} \frac{\sigma_\alpha^2 + \pi^2\sigma^2}{1-\rho_\alpha^2} \qquad \text{(A.28)}
\end{aligned}
$$

Return on consumption claim $r_{c,t+1}$, on dividend paying asset $r_{i,t+1}$ and risk-free rate $r_{f,t}$

Let us determine $z_t = A_0 + A_1 x_t + A_2\sigma_t^2 + A_3\Delta\alpha_{cc,t}$. From the Euler equation 1.15, we have :

$$
\begin{aligned}
1 &= \mathbb{E}_t e^{\theta log\delta - \frac{\theta}{\psi}\Delta c_{t+1} + \theta r_{c,t+1}} \\
&= e^{\mathbb{E}_t(\theta log\delta - \frac{\theta}{\psi}\Delta c_{t+1} + \theta r_{c,t+1}) + 0.5\mathbb{V}_t(\theta log\delta - \frac{\theta}{\psi}\Delta c_{t+1} + \theta r_{c,t+1})} \\
&= e^{\theta log\delta - \frac{\theta}{\psi}\mathbb{E}_t(\Delta c_{t+1}) + \theta\mathbb{E}_t r_{c,t+1} + 0.5\mathbb{V}_t((-\frac{\theta}{\psi}+\theta)\Delta c_{t+1} + \theta\kappa_1 z_{t+1})} \\
&= exp(\theta log\delta + (1-\gamma)(\nu_{cc} + x_t - \nu_\alpha(1-\rho_\alpha) - \rho_\alpha\Delta\alpha_{cc,t}) + \theta(\kappa_0 - A_0 - A_1 x_t - A_2\sigma_t^2 - A_3\Delta\alpha_{cc,t} \\
&+ \theta\kappa_1(A_0 + A_1\rho_x x_t + A_2((1-\nu)\sigma^2 + \nu\sigma_t^2) + A_3(\nu_\alpha(1-\rho_\alpha) + \rho_\alpha\Delta\alpha_{cc,t})) \\
&+ 0.5\left\{\left((1-\gamma+\pi(-1+\gamma+\theta\kappa_1 A_3))^2 + (\theta\kappa_1 A_1)^2\psi_x^2\right)\sigma_t^2 + (-1+\gamma+\theta\kappa_1 A_3)^2\sigma_\alpha^2 + \theta^2\kappa_1^2 A_2^2\sigma_w^2\right\}) \\
0 &= \theta log\delta + (1-\gamma)(\nu_{cc} - \nu_\alpha(1-\rho_\alpha)) + \theta(\kappa_0 - A_0) + \theta\kappa_1(A_0 + A_2(1-\nu)\sigma^2 + A_3\nu_\alpha(1-\rho_\alpha)) \\
&+ 0.5\left\{(-1+\gamma+\theta\kappa_1 A_3)^2\sigma_\alpha^2 + \theta^2\kappa_1^2 A_2^2\sigma_w^2\right\} \\
&+ (1-\gamma-\theta A_1 + \theta\kappa_1 A_1\rho_x)\, x_t \\
&+ \left(-\theta A_2 + \theta\kappa_1 A_2\nu + 0.5\,(1-\gamma+\pi(-1+\gamma+\theta\kappa_1 A_3))^2 + 0.5(\theta\kappa_1 A_1)^2\psi_x^2\right)\sigma_t^2 \\
&+ (-(1-\gamma)\rho_\alpha - \theta A_3 + \theta\kappa_1 A_3\rho_\alpha)\,\Delta\alpha_{cc,t}
\end{aligned}
$$

By identification :

$$
\begin{aligned}
A_1 &= \frac{1-\frac{1}{\psi}}{1-\kappa_1\rho_x} \\
A_3 &= -\frac{\left(1-\frac{1}{\psi}\right)\rho_\alpha}{1-\kappa_1\rho_\alpha} \\
A_2 &= 0.5\theta\frac{\left(1-\frac{1}{\psi}+\pi(-1+\frac{1}{\psi}+\kappa_1 A_3)\right)^2 + (\kappa_1 A_1)^2\psi_x^2}{1-\kappa_1\nu} \\
A_0 &= \frac{log\delta + (1-\frac{1}{\psi})(\nu_{cc} - \nu_\alpha(1-\rho_\alpha)) + \kappa_0 + \kappa_1(A_2(1-\nu)\sigma^2 + A_3\nu_\alpha(1-\rho_\alpha))}{1-\kappa_1} \\
&+ \frac{0.5\theta\left\{\left(-1+\frac{1}{\psi}+\kappa_1 A_3\right)^2\sigma_\alpha^2 + \kappa_1^2 A_2^2\sigma_w^2\right\}}{1-\kappa_1}
\end{aligned}
$$

Let us determine :

$$z_{i,t} = A_{0,i} + A_{1,i}x_t + A_{2,i}\sigma_t^2 + A_{3,i}\Delta\alpha_{cc,t}$$

Let us remind that one can rewrite the return on any asset and its dividend growth process as follow :

$$\begin{aligned} r_{i,t+1} &= \kappa_{0,i} + \kappa_{1,i}z_{i,t+1} - z_{i,t} + \Delta d_{i,t} \\ \Delta d_{i,t+1} &= \nu_i + \phi_i x_t + \phi_{\alpha,i}\Delta\alpha_{cc,t} + \psi_i\sigma_t\epsilon_{i,t+1} \end{aligned}$$

From the Euler equation 1.15, we have :

$$\begin{aligned} 1 &= \mathbb{E}_t e^{\theta log\delta - \frac{\theta}{\psi}\Delta c_{t+1} + (\theta-1)r_{c,t+1} + r_{i,t+1}} \\ &= e^{\mathbb{E}_t(\theta log\delta - \frac{\theta}{\psi}\Delta c_{t+1} + (\theta-1)r_{c,t+1} + r_{i,t+1}) + 0.5\mathbb{V}_t(\theta log\delta - \frac{\theta}{\psi}\Delta c_{t+1} + (\theta-1)r_{c,t+1} + r_{i,t+1})} \\ &= e^{\theta log\delta - \frac{\theta}{\psi}\mathbb{E}_t(\Delta c_{t+1}) + (\theta-1)\mathbb{E}_t r_{c,t+1} + \mathbb{E}_t r_{i,t+1} + 0.5\mathbb{V}_t((-\frac{\theta}{\psi}\Delta c_{t+1} + (\theta-1)r_{c,t+1} + r_{i,t+1})} \\ 0 &= \theta log\delta - \gamma(\nu_{cc} + x_t - \nu_\alpha(1-\rho_\alpha) - \rho_\alpha\Delta\alpha_{cc,t}) + (\theta-1)(\kappa_0 - A_0 - A_1x_t - A_2\sigma_t^2 - A_3\Delta\alpha_{cc,t}) \\ &+ (\theta-1)\kappa_1(A_0 + A_1\rho_x x_t + A_2((1-\nu)\sigma^2 + \nu\sigma_t^2) + A_3(\nu_\alpha(1-\rho_\alpha) + \rho_\alpha\Delta\alpha_{cc,t})) + \kappa_{0,i} \\ &+ \kappa_{1,i}(A_{0,i} + A_{1,i}\rho_x x_t + A_{2,i}((1-\nu)\sigma^2 + \nu\sigma_t^2) + A_{3,i}(\nu_\alpha(1-\rho_\alpha) + \rho_\alpha\Delta\alpha_{cc,t})) + \nu_i + \phi_i x_t + \phi_{\alpha,i}\Delta\alpha_{cc,t} \\ &+ 0.5\left\{(-\gamma + \pi(\gamma + (\theta-1)\kappa_1A_3 + \kappa_{1,i}A_{3,i}))^2 + ((\theta-1)\kappa_1A_1 + \kappa_{1,i}A_{1,i})^2\psi_x^2 + \psi_i^2\right\}\sigma_t^2 \\ &+ 0.5\left(\gamma + (\theta-1)\kappa_1A_3 + \kappa_{1,i}A_{3,i}\right)^2\sigma_\alpha^2 \\ &+ 0.5\left((\theta-1)\kappa_1A_2 + \kappa_{1,i}A_{2,i}\right)^2\sigma_w^2 - A_{0,i} - A_{1,i}x_t - A_{2,i}\sigma_t^2 - A_{3,i}\Delta\alpha_{cc,t} \\ 0 &= \theta log\delta - \gamma(\nu_{cc} - \nu_\alpha(1-\rho_\alpha)) + (\theta-1)(\kappa_0 - A_0) + (\theta-1)\kappa_1(A_0 + A_2(1-\nu)\sigma^2 + A_3\nu_\alpha(1-\rho_\alpha)) + \kappa_{0,i} \\ &+ \kappa_{1,i}(A_{0,i} + A_{2,i}(1-\nu)\sigma^2 + A_{3,i}\nu_\alpha(1-\rho_\alpha)) + \nu_i \\ &+ 0.5\left(\gamma + (\theta-1)\kappa_1A_3 + \kappa_{1,i}A_{3,i}\right)^2\sigma_\alpha^2 + 0.5\left((\theta-1)\kappa_1A_2 + \kappa_{1,i}A_{2,i}\right)^2\sigma_w^2 - A_{0,i} \\ &+ \left(-\gamma - (\theta-1)A_1 + (\theta-1)\kappa_1A_1\rho_x + \kappa_{1,i}A_{1,i}\rho_x + \phi_i - A_{1,i}\right)x_t \\ &+ \left(0.5((-\gamma + \pi(\gamma + (\theta-1)\kappa_1A_3 + \kappa_{1,i}A_{3,i}))^2 + ((\theta-1)\kappa_1A_1 + \kappa_{1,i}A_{1,i})^2\psi_x^2 + \psi_i^2)\right)\sigma_t^2 \\ &+ \left(-(\theta-1)A_2 + (\theta-1)\kappa_1A_2\nu + \kappa_{1,i}A_{2,i}\nu - A_{2,i}\right)\sigma_t^2 \\ &+ \left(\gamma\rho_\alpha - (\theta-1)A_3 + (\theta-1)\kappa_1A_3\rho_\alpha + \kappa_{1,i}A_{3,i}\rho_\alpha + \phi_{\alpha,i} - A_{3,i}\right)\Delta\alpha_{cc,t} \end{aligned}$$

By identification :

$$A_{1,i} = \frac{\phi_i - \dfrac{1}{\psi}}{1 - \kappa_{1,i}\rho_x}$$

$$A_{3,i} = \frac{\phi_{\alpha,i} + \dfrac{\rho_\alpha}{\psi}}{1 - \kappa_{1,i}\rho_\alpha}$$

$$A_{2,i} = \frac{(1-\theta)A_2(1-\kappa_1\nu) + 0.5\left\{(-\gamma + \pi(\gamma + (\theta-1)\kappa_1 A_3 + \kappa_{1,i}A_{3,i}))^2 + ((\theta-1)\kappa_1 A_1 + \kappa_{1,i}A_{1,i})^2\psi_x^2 + \right.}{1 - \kappa_{1,i}\nu}$$

$$A_{0,i} = \frac{\theta log\delta - \gamma(\nu_{cc} - \nu_\alpha(1-\rho_\alpha)) + (\theta-1)(\kappa_0 - A_0) + (\theta-1)\kappa_1(A_0 + A_2(1-\nu)\sigma^2 + A_3\nu_\alpha(1-\rho_\alpha)) +}{1-\kappa_{1,i}}$$
$$+ \frac{\kappa_{1,i}(A_{2,i}(1-\nu)\sigma^2 + A_{3,i}\nu_\alpha(1-\rho_\alpha)) + \nu_i}{1-\kappa_{1,i}}$$
$$+ \frac{0.5\left(\gamma + (\theta-1)\kappa_1 A_3 + \kappa_{1,i}A_{3,i}\right)^2\sigma_\alpha^2 + 0.5\left((\theta-1)\kappa_1 A_2 + \kappa_{1,i}A_{2,i}\right)^2\sigma_w^2}{1-\kappa_{1,i}}$$

Deriving $r_{f,t}$:

$$\mathbb{E}_t e^{\theta log\delta - \frac{\theta}{\psi}\Delta c_{t+1} + (\theta-1)r_{c,t+1} + r_{f,t}} = 1$$

So

$$e^{-r_{f,t}} = \mathbb{E}_t e^{\theta log\delta - \frac{\theta}{\psi}\Delta c_{t+1} + (\theta-1)r_{c,t+1}}$$
$$= e^{\mathbb{E}_t(\theta log\delta - \frac{\theta}{\psi}\Delta c_{t+1} + (\theta-1)r_{c,t+1}) + 0.5\mathbb{V}_t(\theta log\delta - \frac{\theta}{\psi}\Delta c_{t+1} + (\theta-1)r_{c,t+1})}$$
$$= e^{\theta log\delta - \frac{\theta}{\psi}\mathbb{E}_t(\Delta c_{t+1}) + (\theta-1)\mathbb{E}_t r_{c,t+1} + 0.5\mathbb{V}_t((-\frac{\theta}{\psi}\Delta c_{t+1} + (\theta-1)r_{c,t+1})}$$

$$-r_{f,t} = \theta log\delta - \gamma(\nu_{cc} + x_t - \nu_\alpha(1-\rho_\alpha) - \rho_\alpha\Delta\alpha_{cc,t}) + (\theta-1)(\kappa_0 - A_0 - A_1 x_t - A_2\sigma_t^2 - A_3\Delta\alpha_{cc,t})$$
$$+ (\theta-1)\kappa_1(A_0 + A_1\rho_x x_t + A_2((1-\nu)\sigma^2 + \nu\sigma_t^2) + A_3(\nu_\alpha(1-\rho_\alpha) + \rho_\alpha\Delta\alpha_{cc,t}))$$
$$+ 0.5\left\{(-\gamma + \pi(\gamma + (\theta-1)\kappa_1 A_3))^2 + ((\theta-1)\kappa_1 A_1)^2\psi_x^2\right\}\sigma_t^2$$
$$+ 0.5\left(\gamma + (\theta-1)\kappa_1 A_3\right)^2\sigma_\alpha^2 + 0.5\left((\theta-1)\kappa_1 A_2\right)^2\sigma_w^2$$

$$-r_{f,t} = \theta log\delta - \gamma(\nu_{cc} - \nu_\alpha(1-\rho_\alpha)) + (\theta-1)(\kappa_0 - A_0) + (\theta-1)\kappa_1(A_0 + A_2(1-\nu)\sigma^2 + A_3\nu_\alpha(1-\rho_\alpha))$$
$$+ 0.5\left(\gamma + (\theta-1)\kappa_1 A_3\right)^2\sigma_\alpha^2 + 0.5\left((\theta-1)\kappa_1 A_2\right)^2\sigma_w^2$$
$$+ \left(-\gamma - (\theta-1)A_1 + (\theta-1)\kappa_1 A_1\rho_x\right)x_t$$
$$+ \left(-(\theta-1)A_2 + (\theta-1)\kappa_1 A_2\nu + 0.5((-\gamma + \pi(\gamma + (\theta-1)\kappa_1 A_3))^2 + ((\theta-1)\kappa_1 A_1)^2\psi_x^2)\right)\sigma_t^2$$
$$+ \left(\gamma\rho_\alpha - (\theta-1)A_3 + (\theta-1)\kappa_1 A_3\rho_\alpha\right)\Delta\alpha_{cc,t}$$

Therefore :

$$r_{f,t} = A_{0,f} + A_{1,f}x_t + A_{2,f}\sigma_t^2 + A_{3,f}\Delta\alpha_{cc,t}$$

Deriving $\mathbb{E}_t r_{i,t+1}$:

$$\begin{aligned}\mathbb{E}_t r_{i,t+1} =& \kappa_{0,i} + \kappa_{1,i}\mathbb{E}_t z_{i,t+1} - A_{0,i} - A_{1,i}x_t - A_{2,i}\sigma_t^2 - A_{3,i}\Delta\alpha_{cc,t} + \nu_i + \phi x_t + \phi_{\alpha,i}\Delta\alpha_{cc,t}\\ =& \kappa_{0,i} + \kappa_{1,i}\mathbb{E}_t(A_{0,i} + A_{1,i}x_{t+1} + A_{2,i}\sigma_{t+1}^2 + A_{3,i}\Delta\alpha_{cc,t+1})\\ &- A_{0,i} - A_{1,i}x_t - A_{2,i}\sigma_t^2 - A_{3,i}\Delta\alpha_{cc,t} + \nu_i + \phi_i x_t + \phi_{\alpha,i}\Delta\alpha_{cc,t}\\ =& \kappa_{0,i} + \kappa_{1,i}A_{0,i} + \kappa_{1,i}A_{1,i}\rho_x x_t + \kappa_{1,i}A_{2,i}((1-\nu^2)\sigma^2 + \nu\sigma_t^2)\\ &+ \kappa_{1,i}A_{3,i}(\nu_\alpha(1-\rho_\alpha) + \rho_\alpha\Delta\alpha_{cc,t}) - A_{0,i} - A_{1,i}x_t - A_{2,i}\sigma_t^2 - A_{3,i}\Delta\alpha_{cc,t} + \nu_i + \phi_i x_t + \phi_{\alpha,i}\Delta\alpha_{cc}\\ =& \kappa_{0,i} + \kappa_{1,i}A_{0,i} + \kappa_{1,i}A_{2,i}(1-\nu)\sigma^2 + \kappa_{1,i}A_{3,i}\nu_\alpha(1-\rho_\alpha) - A_{0,i} + \nu_i\\ &+ (-A_{1,i} + \phi_i + \kappa_{1,i}A_{1,i}\rho_x)x_t + (-A_{2,i} + \kappa_{1,i}A_{2,i}\nu)\sigma_t^2 + (-A_{3,i} + \phi_{\alpha,i} + \kappa_{1,i}A_{3,i}\rho_\alpha)\Delta\alpha_{cc,t}\\ =& B_0 + B_1 x_t + B_2\sigma_t^2 + B_3\Delta\alpha_{cc,t}\end{aligned}$$

The innovation in the market return is :

$$r_{i,t+1} - \mathbb{E}_t r_{i,t+1} = \kappa_{1,i}A_{1,i}\psi_x\sigma_t\epsilon_{x,t+1} + \kappa_{1,i}A_{2,i}\sigma_w\epsilon_{\sigma,t+1} + \kappa_{1,i}A_{3,i}\sigma_\alpha\epsilon_{\alpha,t+1} + \kappa_{1,i}A_{3,i}\pi\sigma_t\epsilon_{cc,t+1} + \psi_i\sigma_t\epsilon_{i,t+1}$$

So the expected equity premium on any dividend paying asset i is given by :

$$\begin{aligned}\mathbb{E}_t(r_{i,t+1} - r_{f,t}) &= -Cov(r_{i,t+1} - \mathbb{E}_t r_{i,t+1}, m_{t+1} - \mathbb{E}_t m_{t+1}) - 0.5\mathbb{V}_t(r_{i,t+1})\\ &= \lambda_{m,x}\underbrace{\kappa_{1,i}A_{1,i}\psi_x}_{\beta_{i,x}}\sigma_t^2 + \lambda_{m,w}\underbrace{\kappa_{1,i}A_{2,i}}_{\beta_{i,w}}\sigma_w^2 + \lambda_{m,\alpha}\underbrace{\kappa_{1,i}A_{3,i}}_{\beta_{i,\alpha}}\sigma_\alpha^2 + \lambda_{m,cc}\underbrace{\kappa_{1,i}A_{3,i}\pi}_{\beta_{i,cc}}\sigma_t^2 - 0.5\mathbb{V}_t(r_{i,t}\end{aligned}$$

And

$$\begin{aligned}\mathbb{V}_t(r_{i,t+1}) =& \mathbb{V}_t(\kappa_{1,i}z_{i,t+1} + \Delta d_{i,t+1})\\ =& \left(\kappa_{1,i}^2A_{1,i}^2\psi_x^2 + \pi^2\kappa_{1,i}^2A_{3,i}^2 + \psi_i^2\right)\sigma_t^2 + \kappa_{1,i}^2A_{2,i}^2\sigma_w^2 + \kappa_{1,i}^2A_{3,i}^2\sigma_\alpha^2\\ =& (\beta_{i,x}^2 + \beta_{i,cc}^2 + \psi_i^2)\sigma_t^2 + \beta_{i,w}^2\sigma_w^2 + \beta_{i,\alpha}^2\sigma_\alpha^2\end{aligned}$$

A.4 Impulse Response Functions (IRF)

$$x_{t+h} = \Psi_x \sum_{j=0}^{\infty} \rho_x^j \sigma_{t+h-j-1} \epsilon_{x,t+h-j} \tag{A.29}$$

$$\sigma_{t+h}^2 = \sigma^2 + \sigma_w \sum_{j=0}^{\infty} \nu^j \epsilon_{\sigma,t+h-j} \tag{A.30}$$

$$\Delta\alpha_{cc,t+h} = \nu_\alpha + \sigma_\alpha \sum_{j=0}^{\infty} \rho_\alpha^j \epsilon_{\alpha,t+h-j} + \pi \sum_{j=0}^{\infty} \rho_\alpha^j \sigma_{t+h-j-1} \epsilon_{cc,t+h-j} \tag{A.31}$$

$$\Delta cc_{t+h} = \nu_{cc} + x_{t+h-1} + \sigma_{t+h-1} \epsilon_{cc,t+h} \tag{A.32}$$

$$\Delta d_{i,t+h} = \nu_i + \phi_i x_{t+h-1} + \phi_{\alpha,i} \Delta\alpha_{cc,t+h-1} + \Psi_i \sigma_{t+h-1} \epsilon_{i,t+h} \tag{A.33}$$

$$z_{i,t+h} = A_{0,i} + A_{1,i} x_{t+h} + A_{2,i} \sigma_{t+h}^2 + A_{3,i} \Delta\alpha_{cc,t+h} \tag{A.34}$$

$$r_{i,t+h} = \kappa_{0,i} + \kappa_{1,i} z_{i,t+h} - z_{i,t+h-1} + \Delta d_{i,t+h} \tag{A.35}$$

$$r_{f,t+h} = A_{0,f} + A_{1,f} x_{t+h} + A_{2,f} \sigma_{t+h}^2 + A_{3,f} \Delta\alpha_{cc,t+h} \tag{A.36}$$

A.5 Tables

Table A.1: Descriptive statistics : 1930-1955.

	$E(.)$	$\sigma(.)$	$\rho(1)$	$\rho(2)$	$\rho(3)$	$\rho(4)$	$\rho(5)$	CV
Δd	0.0038	0.1914	0.1244	-0.2814	-0.1927	-0.1018	0.0954	50.6037
Δc	0.0169	0.0540	0.3633	0.1214	-0.1689	-0.2447	0.0208	3.1977
$\Delta\alpha_{cc}$	0.0005	0.0231	0.4800	0.0383	-0.1503	-0.3388	-0.2569	50.1958
Δcc	0.0173	0.0611	0.2899	-0.0096	-0.2380	-0.2580	0.0343	3.5250
$\Delta\alpha_{gc}$	-0.0009	0.0378	0.4771	0.0408	-0.0949	-0.3182	-0.2775	-42.0192
Δgc	0.0160	0.0621	0.5495	0.2875	-0.0174	-0.2748	-0.1701	3.8876
z_m	2.8535	0.2265	0.4185	-0.0828	-0.2764	-0.4030	-0.2802	0.0794
r_m	0.0732	0.2468	0.0904	-0.2068	-0.0779	-0.2504	-0.0288	3.3692
r_f	-0.0103	0.0558	0.6365	0.1463	0.0169	0.1026	0.2074	-5.4163

The table reports the sample mean, standard deviation, and first-order to fifth-order autocorrelation of the marketwide log price-dividend ratio, the log dividend, consumption, and the (share of) carbon/green consumption growth rates.

Table A.2: Descriptive statistics : 1956-1980.

	$E(.)$	$\sigma(.)$	$\rho(1)$	$\rho(2)$	$\rho(3)$	$\rho(4)$	$\rho(5)$	CV
Δd	0.0074	0.0523	0.2667	0.0359	0.0091	0.0667	0.0053	7.0994
Δc	0.0222	0.0290	-0.0204	-0.2613	-0.0383	0.0427	0.1899	1.3081
$\Delta\alpha_{cc}$	-0.0035	0.0043	-0.2815	-0.0210	0.3359	-0.3975	0.0456	-1.2429
Δcc	0.0187	0.0295	-0.0577	-0.2755	-0.0490	0.0381	0.1629	1.5790
$\Delta\alpha_{gc}$	0.0061	0.0076	-0.2780	-0.0079	0.3276	-0.3867	0.0584	1.2326
Δgc	0.0283	0.0296	0.0243	-0.2123	0.0213	0.0111	0.2276	1.0473
z_m	3.2918	0.1822	0.6555	0.3480	0.2547	0.3035	0.1185	0.0553
r_m	0.0445	0.1779	-0.0762	-0.3736	0.1056	0.3032	0.0922	4.0023
r_f	0.0030	0.0152	0.5917	0.4075	0.4660	0.3126	0.2736	5.0496

The table reports the sample mean, standard deviation, and first-order to fifth-order autocorrelation of the marketwide log price-dividend ratio, the log dividend, consumption, and the (share of) carbon/green consumption growth rates.

Table A.3: Descriptive statistics : 1981-2018.

	$E(.)$	$\sigma(.)$	$\rho(1)$	$\rho(2)$	$\rho(3)$	$\rho(4)$	$\rho(5)$	CV
Δd	0.0339	0.0926	-0.0365	-0.0047	-0.0714	-0.1272	-0.0885	2.7331
Δc	0.0155	0.0162	0.4603	0.0530	-0.0526	-0.0848	-0.0747	1.0438
$\Delta\alpha_{cc}$	-0.0052	0.0066	0.3599	-0.0832	-0.2421	-0.0687	0.1352	-1.2812
Δcc	0.0104	0.0185	0.5090	0.0042	-0.1916	-0.1590	-0.1158	1.7807
$\Delta\alpha_{gc}$	0.0065	0.0083	0.3914	-0.0141	-0.1654	0.0388	0.1809	1.2843
Δgc	0.0220	0.0172	0.3744	0.1211	0.1178	0.0675	0.0877	0.7844
z_m	3.8166	0.4151	0.8895	0.7548	0.6669	0.5546	0.4293	0.1088
r_m	0.0831	0.1618	-0.0695	-0.1204	0.0703	-0.0356	-0.4177	1.9464
r_f	0.0109	0.0221	0.7975	0.6500	0.5337	0.3759	0.3189	2.0303

The table reports the sample mean, standard deviation, and first-order to fifth-order autocorrelation of the marketwide log price-dividend ratio, the log dividend, consumption, and the (share of) carbon/green consumption growth rates.

Table A.4: Model-implied moments.

		$\sigma(z_m)$	EP	$E(R_f)$	$\sigma(r_{m,a})$	$\sigma(r_{f,a})$	$\rho(z_m)$
1930-1955							
	Data	0.227	0.084	-0.010	0.247	0.010	0.418
BY2004	Mean	0.238	0.109	0.007	0.264	0.159	0.354
	5%	0.166	-0.019	-0.051	0.193	0.122	0.019
	50%	0.234	0.105	0.006	0.261	0.158	0.368
	95%	0.325	0.251	0.065	0.346	0.198	0.637
LRCCR	Mean	0.150	0.040	0.010	0.116	0.019	0.608
	5%	0.098	0.000	-0.005	0.089	0.014	0.291
	50%	0.145	0.039	0.010	0.115	0.018	0.635
	95%	0.216	0.081	0.024	0.144	0.025	0.834
1956-1980							
	Data	0.182	0.041	0.003	0.178	0.003	0.656
BY2004	Mean	0.125	0.093	-0.002	0.134	0.001	0.345
	5%	0.093	0.045	-0.002	0.102	0.001	0.019
	50%	0.124	0.093	-0.002	0.133	0.001	0.360
	95%	0.162	0.143	-0.001	0.167	0.002	0.620
LRCCR	Mean	0.175	0.068	0.003	0.197	0.019	0.282
	5%	0.119	0.003	-0.005	0.138	0.014	-0.041
	50%	0.172	0.066	0.003	0.194	0.019	0.293
	95%	0.240	0.141	0.010	0.263	0.024	0.569

The table reports the model-implied moments (the equity premium (EP), the mean of the risk-free rate, the standard deviations of the log price-dividend ratio, the market return, and the risk-free rate, and the first-order autocorrelation of the log price-dividend ratio), alongside some-20 quantiles.

Table A.5: Testing the difference in terms of CS R^2

Industries

	Δcc	$\Delta\alpha_{cc}$	$\Delta cc + \Delta\alpha_{cc}$	Δgc	$\Delta\alpha_{gc}$	$\Delta gc + \Delta\alpha_{gc}$	Δc
$R^2_{ff3} - R^2_{ff3+new}$	-0.027	-0.002	-0.028	-0.004	-0.006	-0.027	-0.075
p_{cs}	0.146	0.753	0.391	0.638	0.606	0.446	0.011
p_{ms}	0.248	0.787	0.544	0.692	0.648	0.571	0.059
$p_{wald,cs}$	0.146	0.753	0.241	0.638	0.606	0.305	0.011
$p_{wald,ms}$	0.248	0.787	0.476	0.692	0.648	0.505	0.059
FF25P							
$R^2_{ff3} - R^2_{ff3+new}$	-0.009	-0.100	-0.101	-0.046	-0.092	-0.093	-0.004
p_{cs}	0.294	0.022	0.044	0.076	0.048	0.082	0.510
p_{ms}	0.530	0.074	0.162	0.162	0.096	0.193	0.689
$p_{wald,cs}$	0.294	0.022	0.081	0.076	0.048	0.143	0.510
$p_{wald,ms}$	0.530	0.074	0.221	0.162	0.096	0.267	0.689

This table reports the difference in terms of cross-sectional R^2 and the p-values for the test $H_0 : R^2_{ff3} = R^2_{ff3+new}$. It reports four different p-values: p-value of testing $H_0 : R^2_{ff3} = R^2_{ff3+new}$ under correctly specified model, p-value of testing $H_0 : R^2_{ff3} = R^2_{ff3+new}$ under misspecified model, p-value of Wald test of $H_0 : R^2_{ff3} = R^2_{ff3+new}$ under correctly specified model, and p-value of Wald test of $H_0 : R^2_{ff3} = R^2_{ff3+new}$ under potentially misspecified model.The models are estimated using annual returns on the 25 Fama–French size and book-to-market ranked portfolios and 42 industry portfolios. The data are from 1930 to 2018.

Table A.6: Means, and t-statistics for monthly factor returns over different samples.

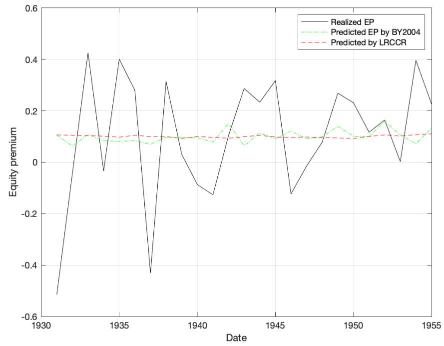
This table reports the factor's premiums for eight strategies. The first four rows' strategies long/short extreme deciles while the last four long/short firms that have positive/negative betas.

	1930-2018		1930-1980		1981-2018	
	Mean	tstat	Mean	tstat	Mean	tstat
Δcc	0.47	1.74	0.32	0.91	0.66	1.59
$\Delta\alpha_{cc}$	-0.22	-0.91	0.03	0.11	-0.55	-1.39
Δgc	0.4	1.59	0.42	1.28	0.38	0.97
$\Delta\alpha_{gc}$	-0.05	-0.26	-0.37	-1.53	0.35	0.95
$s(\Delta cc)$	0.04	0.53	0.01	0.11	0.08	0.67
$s(\Delta\alpha_{cc})$	0.08	0.96	0.2	1.71	-0.08	-0.77
$s(\Delta gc)$	-0.01	-0.11	-0.02	-0.15	0.00	0.01
$s(\Delta\alpha_{gc})$	0.09	1.23	-0.02	-0.18	0.23	2.07
Mkt-RF	0.63	3.87	0.64	2.68	0.64	3.13
SMB	0.25	2.53	0.37	2.78	0.11	0.74
HML	0.37	3.45	0.42	2.66	0.32	2.3

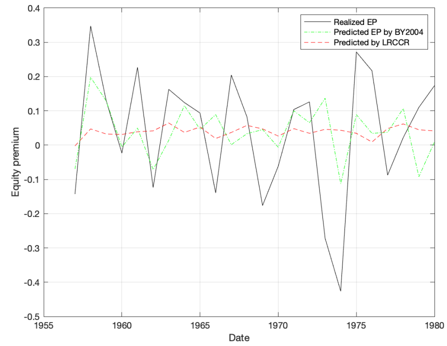
A.6 Figures

Figure A.1: Realized versus predicted equity premium, consumption growth, and dividend growth.

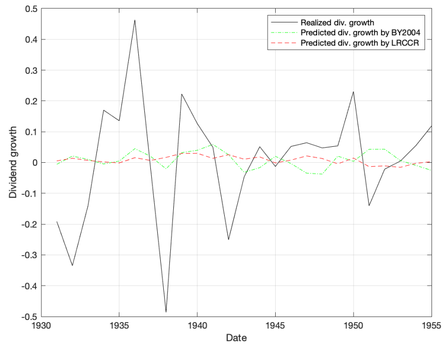
In this figure, I predict equity premium, consumption growth, and dividend growth using the long-run risk derived from my model and compared it to BY model.



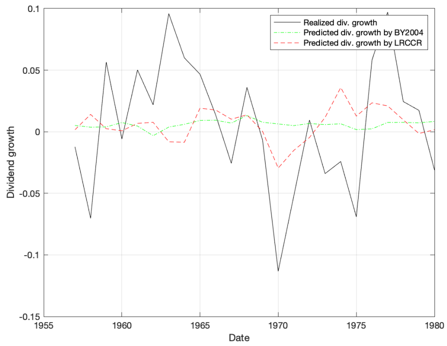
(a) 1930-1955



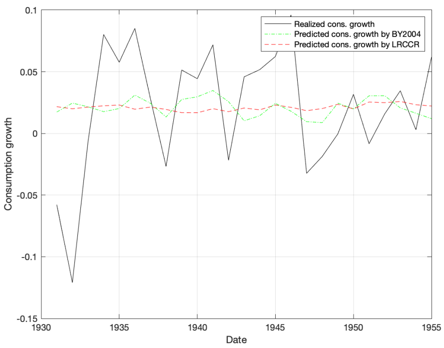
(b) 1956-1980



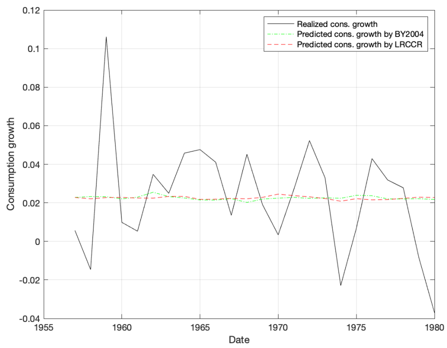
(c) 1930-1955



(d) 1956-1980



(e) 1930-1955



(f) 1956-1980

Figure A.2: IRF: 1981-2018.

In this figure, I plot the impulse response functions of consumption growth, carbon consumption growth, share of carbon consumption growth, price dividend ratio, market return, and risk free rate following one standard deviation shock (increase) to the expected carbon consumption.

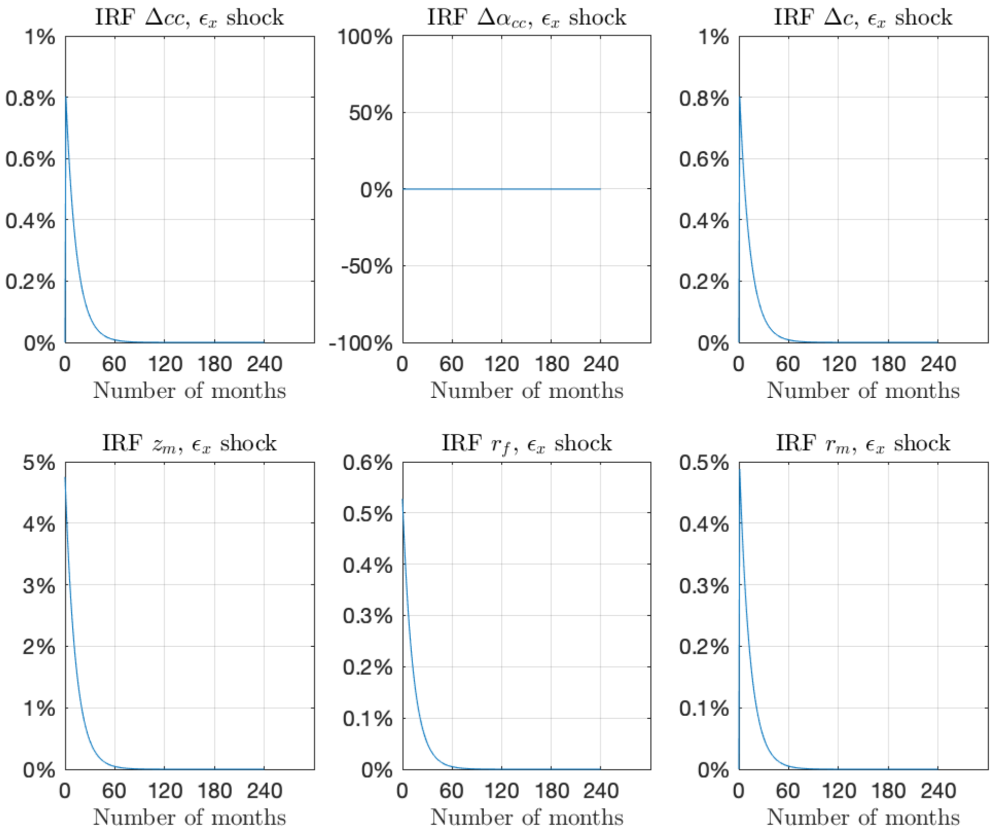
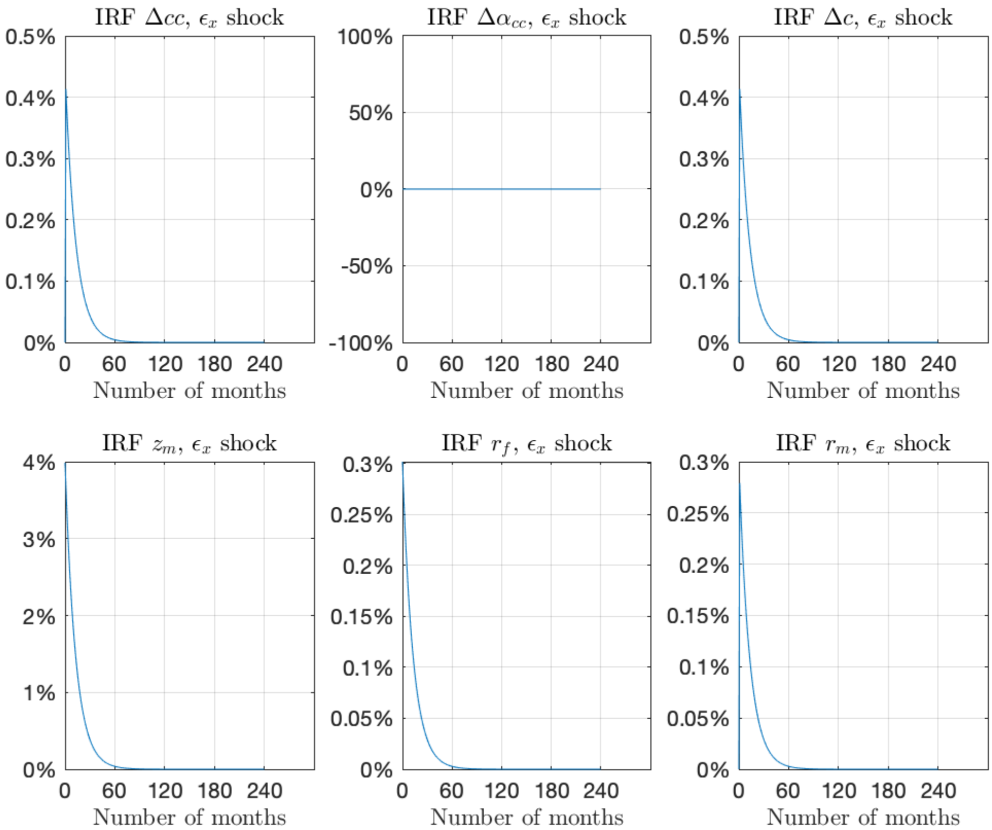


Figure A.3: IRF: 1930-2018.

In this figure, I plot the impulse response functions of consumption growth, carbon consumption growth, share of carbon consumption growth, price dividend ratio, market return, and risk free rate following one standard deviation shock (increase) to the expected carbon consumption.



A.7 Data construction details

Table A.7: Carbon footprint covered from the NIPA expenditure data.

Household consumption expenditures category (2 digit level)	**Footprint Covererage E**
1-Food and beverages purchased for off-premises consumption	
Food and nonalcoholic beverages purchased for off-premises consumption	√
Alcoholic beverages purchased for off-premises consumption	x
Food produced and consumed on farms	√
2-Clothing, footwear, and related services	
Clothing	√
Footwear	√
3-Housing, utilities, and fuels	
Housing	√
Household utilities and fuels	
Water supply and sanitation	√
Electricity, gas, and other fuels	x
Electricity	√
Natural gas	√
Fuel oil and other fuels	
4-Furnishings, household equipment, and routine household maintenance	
Furniture, furnishings, and floor coverings	√
Household textiles	√
Household appliances	√
Glassware, tableware, and household utensils	√
Tools and equipment for house and garden	x
5-Health	
Medical products, appliances, and equipment	x
Outpatient services	√
Hospital and nursing home services	
Hospital	√
Nursing home services	√
6-Transportation	
Motor vehicles	√
Motor vehicle operation	√
Public transportation	
Ground transportation	√
Air transportation	√
Water transportation	√
7-Communication	
Telephone and related communication equipment	√
Postal and delivery services	√
Telecommunication services	√
Internet access	x
8-Recreation	
Video and audio equipment, computers, and related services	√
Sports and recreational goods and related services	√
Membership clubs, sports centers, parks, theaters, and museums	√
Magazines, newspapers, books, and stationery	√
Gambling	x
Pets, pet products, and related services	x
Photographic goods and services	x
Package tours	x
9-Education	
Educational books	x
Higher education	√
Nursery, elementary, and secondary schools	√
Commercial and vocational schools	√
10-Food services and accommodations	
Food services	√
Accommodations	√
11-Financial services and insurance	
Financial services	√
Insurance	√

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Table A.7 – continued from previous page

Household consumption expenditures category (2 digit level)	**Footprint Covererage E**
12-Other goods and services	
Personal care	$\surd$
Personal items	$\surd$
Social services and religious activities	$\surd$
Professional and other services	$\surd$
Tobacco	$\surd$

Appendix B

Appendix to Chapter 2

B.1 Tables

Table B.1: List of anomalies.

Abbreviation (rebalanced)	Name of the anomaly
accruals (annually)	Accruals Follows Sloan (1996).
agrowth (annually)	Asset Growth Follows Cooper et al. (2008).
aturnover (annually)	Asset Turnover Follows Soliman (2008).
cfp (annually)	Cash Flow / Market Value of Equity Follows Lakonishok et al. (1994).
ciss (monthly)	Composite Issuance Follows Daniel and Titman (2006).
ep (annually)	Earnings/Price Follows Basu (1977).
gltnoa (annually)	Growth in LTNOA Follows Fairfield et al. (2003).
gmargins (annually)	Gross Margins Follows Novy-Marx (2013).
inv (annually)	Investment Follows Chen et al. (2011).
igrowth (annually)	Invetment Growth Follows Xing (2008).
invcap (annually)	Investment-to-Capital Follows Xing (2008).
indmomrev (monthly)	Industry Momentum-Reversal Follows Moskowitz and Grinblatt (1999).
indrrev (monthly)	Industry Relative Reversals Follows Da et al. (2014).
indrrevlv (monthly)	Industry Relative Reversals (Low Volatility) Follows Da et al. (2014).
lrrev (monthly)	Long-term Reversals Follows De Bondt and Thaler (1985).
mom11 (monthly)	Momentum (11m) Follows Jegadeesh and Titman (1993).
mom6 (monthly)	Momentum (6m) Follows Jegadeesh and Titman (1993).
indmom (monthly)	Industry Momentum Follows Moskowitz and Grinblatt (1999).
valmom (monthly)	Value-Momentum Follows Novy-Marx (2013).
momrev (monthly)	Momentum-Reversal Follows Jegadeesh and Titman (1993).
nissa (annually)	Share Issuance (annual) Follows Pontiff and Woodgate (2008).
noa (annually)	Net Operating Assets Follows Hirshleifer et al. (2004).
noaa (annually)	Net Operating Assets Follows Kozak et al. (2020).
price (monthly)	Follows Blume and Husic (1973).
roa (quarterly)	Return on Assets Follows Chen et al. (2011).
roaa (annually)	Return on Assets (annual) Follows Chen et al. (2011).
roe (monthly)	Return on Book Equity Follows Chen et al. (2011).
season (monthly)	Seasonality Follows Heston and Sadka (2008).
sgrowth (annually)	Sales Growth Follows Lakonishok et al. (1994).
shvol (monthly)	Share Volume Follows Datar et al. (1998).
size (annually)	Follows Fama and French (1993).
strev (monthly)	Short-term Reversal Follows Jegadeesh (1990).
sue (monthly)	Standardized Unexpected Earning Follows Foster et al. (1984).
value (annually)	Follows Fama and French (1993).
valuem (monthly)	Value (monthly) Follows Asness et al. (2013).
prof (annually)	Gross Profitability Follows Novy-Marx (2013).
valprof (monthly)	Value-Profitability Follows Novy-Marx (2013).

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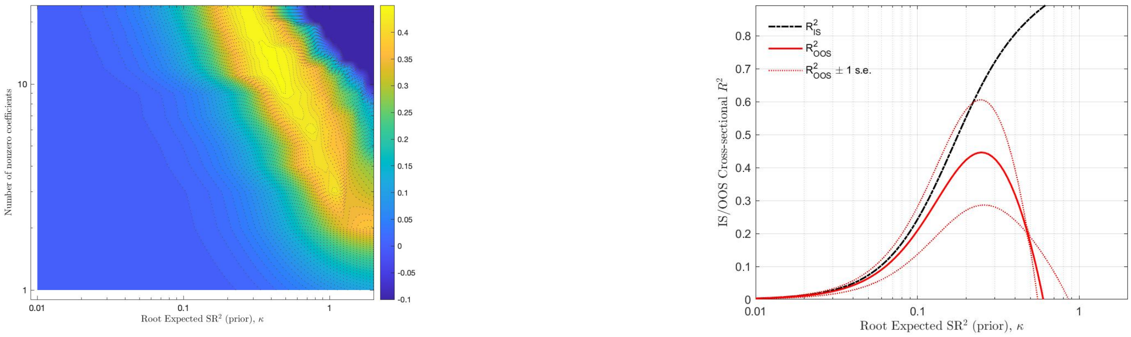
Table B.1 – continued from previous page

Abbreviation (rebalanced)	Name of the anomaly
F-score (annually)	Piotroski's F -score Follows Piotroski (2000).
debtiss (annually)	Debt Issuance Follows Spiess and Affleck-Graves (1999).
repurch (annually)	Share Repurchases Follows Ikenberry et al. (1995).
divp (annually)	Dividend Yield Follows Naranjo et al. (1998).
divg (annually)	Dividend growth Follows Giglio et al. (2021a)
dur (annually)	Cash flow duration Follows Giglio et al. (2021a)
lev (annually)	Leverage Follows Bhandari (1988).
sp (annually)	Sales-to-Price Follows Barbee et al. (1996).
valmomprof (monthly)	Value-Momentum-Profitability Follows Novy-Marx (2013).
shortint (monthly)	Short Interest Follows Dechow et al. (1998).
nissm (monthly)	Share Issuance Follows Pontiff and Woodgate (2008).
rome (monthly)	Return on Market Equity Follows Chen et al. (2011).
ivol (monthly)	Idiosyncratic Volatility Follows Ang et al. (2006).
betaarb (monthly)	Beta Arbitrage Follows Cooper et al. (2008).
age (monthly)	Firm Age Follows Barry and Brown (1984).

Table B.2: Comparison of Linear and Nonlinear Specifications.

	25RR	25LF	HM	3FF	2NL
R^2_{oos}	0.4403	0.4948	0.6765	0.5387	0.6184
κ	0.4011	0.2913	0.3149	0.1706	0.3430
SR	0.501	0.4758	0.7788	0.4610	0.3553

B.2 Figures



(a) Dual penalty (b) L2 penalty

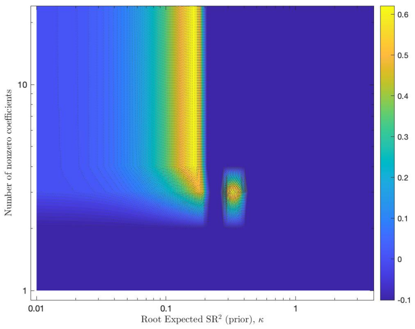
Figure B.1: Raw 25 anomaly portfolios.

In the left panel, we plot in a color map the out-of-sample cross-sectional R^2 (R^2_{oos}) -calculated using 3-fold cross-validation- of the regression of the expected returns on the covariance matrix (risk factors) under the Elastic-Net penalty. In the right panel, we plot the R^2_{oos} (solid red) -calculated using 3-fold cross-validation- and the in-sample cross-sectional R^2_{is} (dashed black) of the regression of the expected returns on the covariance matrix (risk factors) under the Ridge penalty ($\gamma_1 = 0$). The confidence interval of the R^2_{oos}, i.e. $R^2_{oos} \pm 1s.e.$ is drawn with dotted lines.

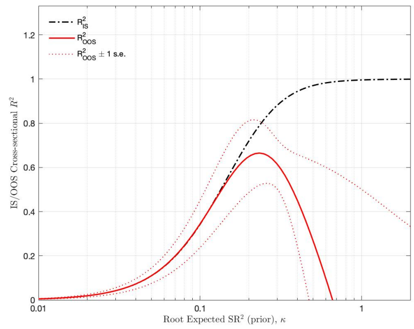
(a) Dual penalty (b) L2 penalty

Figure B.2: PCs 25 anomaly portfolios.

In the left panel, we plot in a color map the out-of-sample cross-sectional R^2 (R^2_{oos}) -calculated using 3-fold cross-validation- of the regression of the expected returns on the covariance matrix (risk factors) under the Elastic-Net penalty. In the right panel, we plot the R^2_{oos} (solid red) -calculated using 3-fold cross-validation- and the in-sample cross-sectional R^2_{is} (dashed black) of the regression of the expected returns on the covariance matrix (risk factors) under the Ridge penalty ($\gamma_1 = 0$). The confidence interval of the R^2_{oos}, i.e. $R^2_{oos} \pm 1s.e.$ is drawn with dotted lines.



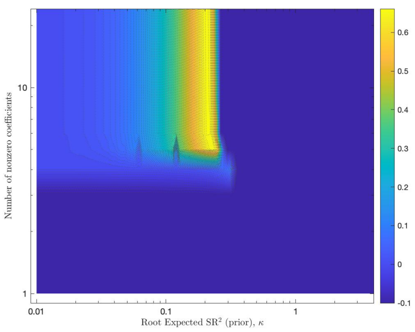
(a) Dual penalty



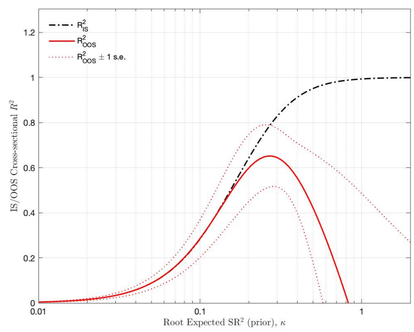
(b) L2 penalty

Figure B.3: Hybrid FF25P using 2 nonlinear factors +23 linear factors.

In the left panel, we plot in a color map the out-of-sample cross-sectional R^2 (R^2_{oos}) -calculated using 3-fold cross-validation- of the regression of the expected returns on the covariance matrix (risk factors) under the Elastic-Net penalty. In the right panel, we plot the R^2_{oos} (solid red) -calculated using 3-fold cross-validation- and the in-sample cross-sectional R^2_{is} (dashed black) of the regression of the expected returns on the covariance matrix (risk factors) under the Ridge penalty ($\gamma_1 = 0$). The confidence interval of the R^2_{oos}, i.e. $R^2_{oos} \pm 1s.e.$ is drawn with dotted lines.



(a) Dual penalty



(b) L2 penalty

Figure B.4: Hybrid FF25P using 3 nonlinear factors +22 linear factors.

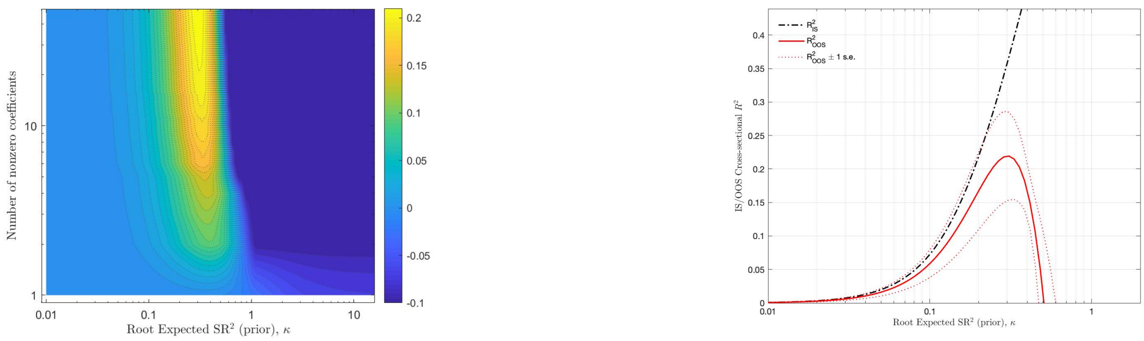
In the left panel, we plot in a color map the out-of-sample cross-sectional R^2 (R^2_{oos}) -calculated using 3-fold cross-validation- of the regression of the expected returns on the covariance matrix (risk factors) under the Elastic-Net penalty. In the right panel, we plot the R^2_{oos} (solid red) -calculated using 3-fold cross-validation- and the in-sample cross-sectional R^2_{is} (dashed black) of the regression of the expected returns on the covariance matrix (risk factors) under the Ridge penalty ($\gamma_1 = 0$). The confidence interval of the R^2_{oos}, i.e. $R^2_{oos} \pm 1s.e.$ is drawn with dotted lines.

(a) Dual penalty

(b) L2 penalty

Figure B.5: Raw 50 anomaly portfolios.

In the left panel, we plot in a color map the out-of-sample cross-sectional R^2 (R^2_{oos}) -calculated using 3-fold cross-validation- of the regression of the expected returns on the covariance matrix (risk factors) under the Elastic-Net penalty. In the right panel, we plot the R^2_{oos} (solid red) -calculated using 3-fold cross-validation- and the in-sample cross-sectional R^2_{is} (dashed black) of the regression of the expected returns on the covariance matrix (risk factors) under the Ridge penalty ($\gamma_1 = 0$). The confidence interval of the R^2_{oos}, i.e. $R^2_{oos} \pm 1s.e.$ is drawn with dotted lines.

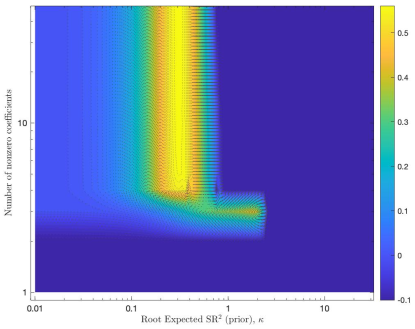


(a) Dual penalty

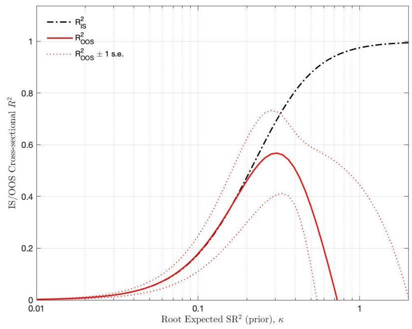
(b) L2 penalty

Figure B.6: PCs 50 anomaly portfolios.

In the left panel, we plot in a color map the out-of-sample cross-sectional R^2 (R^2_{oos}) -calculated using 3-fold cross-validation- of the regression of the expected returns on the covariance matrix (risk factors) under the Elastic-Net penalty. In the right panel, we plot the R^2_{oos} (solid red) -calculated using 3-fold cross-validation- and the in-sample cross-sectional R^2_{is} (dashed black) of the regression of the expected returns on the covariance matrix (risk factors) under the Ridge penalty ($\gamma_1 = 0$). The confidence interval of the R^2_{oos}, i.e. $R^2_{oos} \pm 1s.e.$ is drawn with dotted lines.



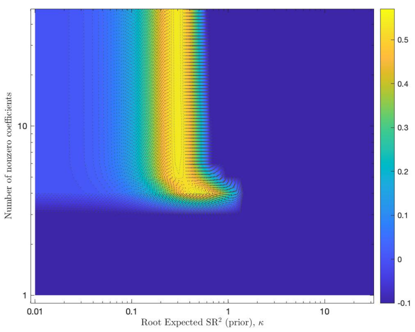
(a) Dual penalty



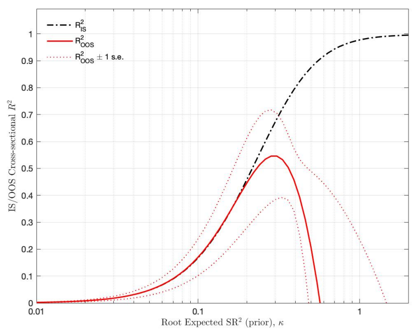
(b) L2 penalty

Figure B.7: Hybrid 50 factors using 2 nonlinear factors +48 linear factors.

In the left panel, we plot in a color map the out-of-sample cross-sectional R^2 (R^2_{oos}) -calculated using 3-fold cross-validation- of the regression of the expected returns on the covariance matrix (risk factors) under the Elastic-Net penalty. In the right panel, we plot the R^2_{oos} (solid red) -calculated using 3-fold cross-validation- and the in-sample cross-sectional R^2_{is} (dashed black) of the regression of the expected returns on the covariance matrix (risk factors) under the Ridge penalty ($\gamma_1 = 0$). The confidence interval of the R^2_{oos}, i.e. $R^2_{oos} \pm 1s.e.$ is drawn with dotted lines.



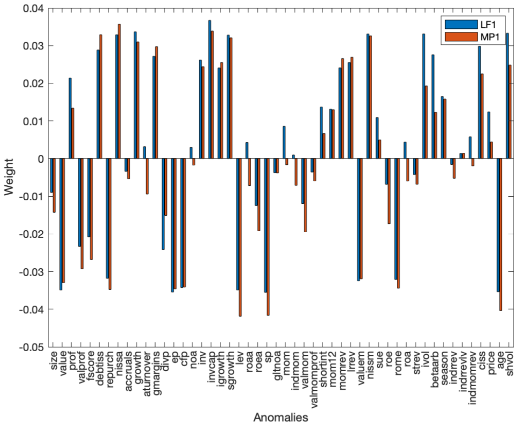
(a) Dual penalty



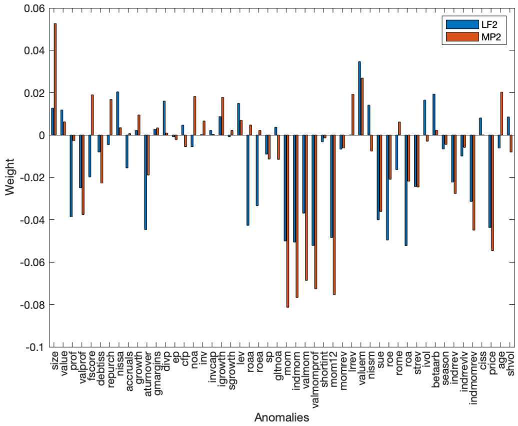
(b) L2 penalty

Figure B.8: Hybrid 50 factors using 3 nonlinear factors +47 linear factors.

In the left panel, we plot in a color map the out-of-sample cross-sectional R^2 (R^2_{oos}) -calculated using 3-fold cross-validation- of the regression of the expected returns on the covariance matrix (risk factors) under the Elastic-Net penalty. In the right panel, we plot the R^2_{oos} (solid red) -calculated using 3-fold cross-validation- and the in-sample cross-sectional R^2_{is} (dashed black) of the regression of the expected returns on the covariance matrix (risk factors) under the Ridge penalty ($\gamma_1 = 0$). The confidence interval of the R^2_{oos}, i.e. $R^2_{oos} \pm 1s.e.$ is drawn with dotted lines.



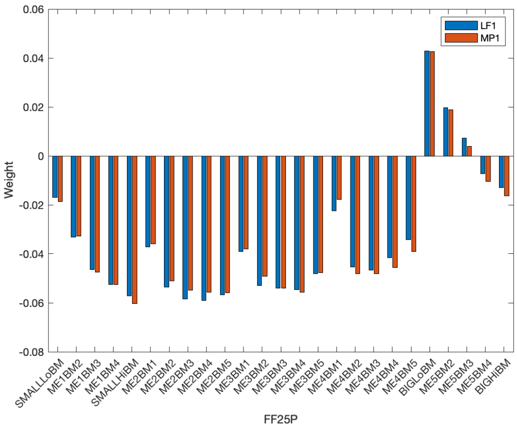
(a) LF1 versus MP1



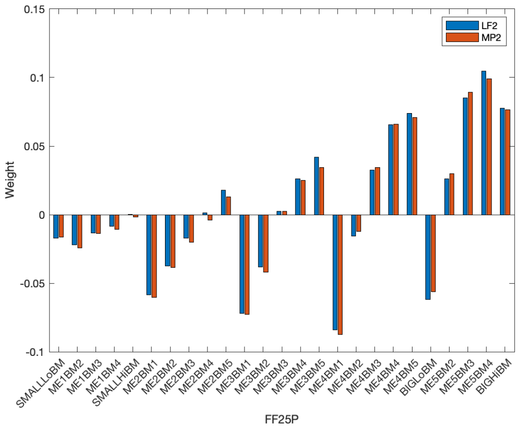
(b) LF2 versus MP2

Figure B.9: 50 anomaly data.

These graphs plot the weight of the anomalies on the first two linear factors and mimicking portfolios.



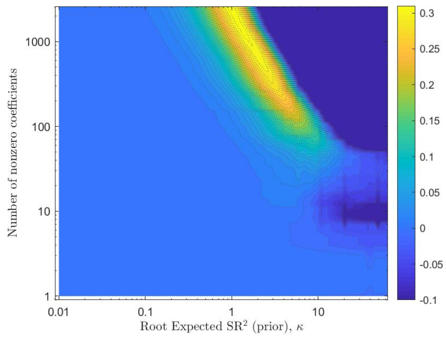
(a) LF1 versus MP1



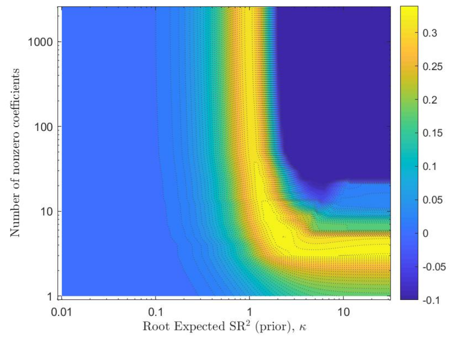
(b) LF2 versus MP2

Figure B.10: FF25P data.

These graphs plot the weight of the 25 Fama-French portfolios on the first two linear factors and mimicking portfolios.



(a) 2600 raw characteristics



(b) PCs of 2600 raw characteristics

Figure B.11: 50 anomaly + interaction terms data.

We plot in a color map the out-of-sample cross-sectional R^2 (R^2_{oos}) -calculated using 3-fold cross-validation- of the regression of the expected returns on the covariance matrix (risk factors) under the Elastic-Net penalty. In the left panel, we rotate the stochastic discount factor in the raw characteristics space and in the right panel, we rotate the stochastic discount factor in the linear principal components space.

B.3 Anomalies

The definitions and descriptions of the anomalies used in this thesis are based on the lists of characteristics compiled by Novy-Marx and Velikov (2016), Haddad et al. (2020), Giglio et al. (2021a) and Kozak et al. (2020).

1. **Accruals (accruals)**:

   Follows Sloan (1996).

   $$accruals = \frac{\Delta ACT - \Delta CHE - \Delta LCT + \Delta DLC + \Delta TXP - \Delta DP}{(AT + AT_{-12})/2}$$

   , where ΔACT is the annual change in total current assets, ΔCHE is the annual change in total cash and short-term investments, ΔLCT is the annual change in current liabilities, ΔDLC is the annual change in debt in current liabilities, ΔTXP is the annual change in income taxes payable, ΔDP is the annual change in depreciation and amortization, and $(AT + AT_{-12})/2$ is average total assets over the last two years. Rebalanced annually.

2. **Asset Growth (agrowth)**:

   Follows Cooper et al. (2008). $agrowth = AT/AT_{-12}$. Rebalanced annually.

3. **Asset Turnover (aturnover)**:

   Follows Soliman (2008). $aturnover = SALE/AT$. Sales to total assets. Rebalanced annually.

4. **Cash Flow / Market Value of Equity (cfp)**:

Follows Lakonishok et al. (1994) $cfp = (IB + DP)/MEDec$. Net income plus depreciation and amortization, all scaled by market value of equity measured at the same date. Rebalanced annually.

5. **Composite Issuance (ciss)**:

   Follows Daniel and Titman (2006). $ciss = \log(\frac{ME_{t-13}}{ME_{t-60}}) - \sum_{l=13}^{60} r_{t-l}$, where r is the log return on the stock and ME is total market equity. Rebalanced monthly.

6. **Earnings/Price (ep)**:

   Follows Basu (1977). $ep = IB/MEDec$. Net income scaled by market value of equity. Rebalanced annually.

7. **Growth in Long Term Net Operating Assets (gltnoa)**:

   Follows Fairfield et al. (2003). $gltnoa = GRNOA - ACC$. Growth in Net Operating Assets minus Accruals. $NOA = (RECT + INVT + ACO + PPENT + INTAN + AO - AP - LCO - LO)/AT$, $GRNOA = NOA - NOA_{-12}$, $ACC = ((RECT - RECT_{-12}) + (INVT - INVT_{-12}) + (ACO - ACO_{-12}) - (AP - AP_{-12}) - (LCO - LCO_{-12}) - DP)/((AT + AT_{-12})/2)$, where $RECT$ = Receivables, $INVT$ = Total Inventory, ACO = Current Assets, AP =Accounts Payable, LCO = Current Liabilities (Other), DP = Depreciation and Amortization, AT = Assets, $PPENT$ = Property, Plant, and Equipment (net), $INTAN$ = Intangible Assets, AO = Assets (Other), LO = Liabilities (Other). Rebalanced annually.

8. **Gross Margins (gmargins)**:

   Follows Novy-Marx (2013). $gmargins = GP/SALE$, where GP is gross profits and $SALE$ is total revenues. Rebalanced annually.

9. **Investment-to-Assets (inv)**:

   Follows Chen et al. (2011). $inv = \frac{PPEGT - PPEGT_{-12} + INVT - INVT_{-12}}{ATQ_{-12}}$. Investment-to-Assets is the annual change in $PPEGTQ$ which is property, plant, and equipment (Compustat item PPEGT) plus annual change in $INVT$ which is total inventories (Compustat item INVT) divided by lagged total assets (AT).

10. **Investment Growth (igrowth)**:

    Follows Xing (2008). $igrowth = CAPX/CAPX_{-12}$. Investment growth is the percentage change in capital expenditure (Compustat item CAPX).

11. **Investment-to-Capital (invcap)**:

    Follows Xing (2008). $invcap = CAPX/PPENT$. Investment to capital is the ratio of capital expenditure ($CAPX$) over property, plant, and equipment ($PPENT$).

12. **Industry Momentum-Reversal (indmomrev)**:

    Follows Moskowitz and Grinblatt (1999). $indmomrev = rank(industrymomentum) + rank(industryrelative{-}reversalslow{-}vol)$. Sum of Fama and French 49 industries ranks on industry momentum and industry relative reversals (low vol). Rebalanced monthly.

13. **Industry Relative Reversals (indrrev)**:

    Follows Da et al. (2014). $indrrev = r_{-1} - r_{-1}^{ind}$, where r is the return on a stock and r^{ind} is return on its industry. Difference between a stocks'prior month's return and the prior month's return of its industry (based on the Fama and French 49 industries). Rebalanced monthly.

14. **Industry Relative Reversals (Low Volatility) (indrrevlv)**:

    Follows Da et al. (2014). $indrrevlv = r - r_{-1}^{ind}$ if $vol < NYSEmedian$, where r is the return on a stock and r^{ind} is return on its industry. Difference between a stocks' prior month's return and the prior month's return of its industry (based on the Fama and French 49 industries). Only stocks with idiosyncratic volatility lower than the NYSE median for month are included in the sorts. Rebalanced monthly.

15. **Long-term Reversals (lrrev)**:

    Follows De Bondt and Thaler (1985). $lrrev = \sum_{l=13}^{60} r_{t-l}$. Cumulative returns from t- 60 to t-13. Rebalanced monthly.

16. **Momentum (11m) (mom11)**:

    Follows Jegadeesh and Titman (1993). $mom11 = \sum_{l=2}^{12} r_{t-l}$. Cumulated past performance in the previous 11 months by skipping the most recent month. Rebalanced monthly.

17. **Momentum (6m) (mom6)**:

    Follows Jegadeesh and Titman (1993). $mom6 = \sum_{l=2}^{7} r_{t-l}$. Cumulated past performance in the previous 6 months by skipping the most recent month. Rebalanced monthly.

18. **Industry Momentum (indmom)**:

    Follows Moskowitz and Grinblatt (1999). $indmom = rank(\sum_{l=1}^{6} r_{t-l}^{ind})$. In each month, the Fama and French 49 industries are sorted on their value-weighted past 6 months' performance and assigned to 10 industry deciles. Then, all firms in decile 10(from the 5 winner industries) form the value-weighted long portfolio and allfirms in decile 1 (the 5 loser industries) form the short portfolio. Rebalanced monthly.

19. **Value-Momentum (valmom)**:

    Follows Novy-Marx (2013). $valmom = rank(B/M) + rank(Mom)$. Sum of ranks in univariate sorts on book-to-market and momentum. Annual book-to-market values are used for the entire year. Rebalanced monthly.

20. **Momentum-Reversal (momrev)**:

    Follows Jegadeesh and Titman (1993). $momrev = \sum_{l=14}^{19} r_{t-l}$. Buy and hold returns from t-19 to t-14. Rebalanced monthly.

21. **Share Issuance (annual) (nissa)**:

Follows Pontiff and Woodgate (2008). $nissa = shrout_{Jun}/shrout_{Jun-12}$, where $shrout$ is the number of shares outstanding. Change in real number of shares outstanding from past June to June of the previous year. Excludes changes in shares due to stock dividends and splits, and companies with no changes in $shrout$.

22. **Net Operating Assets (noa)**:

    Follows Hirshleifer et al. (2004).

    $$noa = (AT - CHE) - (AT - DLC - DLTT - MIB - PSTK - CEQ),$$

    where AT is total assets, CHE is cash and short-term investments, DLC is debt in current liabilities, $DLTT$ is long term debt, MIB is non-controlling interest, $PSTK$ is preferred capital stock, and CEQ is common equity. Rebalanced annually.

23. **Price (price)**:

    Follows Blume and Husic (1973). $price = log(ME/shrout)$, where ME is market equity and $shrout$ is the number of shares outstanding. Log of stock price. Rebalanced monthly.

24. **Return on Assets (roaa)**:

    Follows Chen et al. (2011). $roaa = IB/AT$. Net income scaled by total assets. Rebalanced annually.

25. **Return on Book Equity (roe)**:

    Follows Chen et al. (2011). $roe = IBQ/BEQ_{-3}$, where IBQ is income before extraordinary items (Rebalanced quarterly), and BEQ is book value of equity. Rebalanced monthly.

26. **Seasonality (season)**:

    Follows Heston and Sadka (2008). $season = \sum_{l=1}^{5} r_{t-l\times 12}$. Average monthly return in the same calendar month over the last 5 years. As an example, the average return from prior Octobers is used to predict returns this October. The firm needs at least one year of data to be included in the sample. Rebalanced monthly.

27. **Sales Growth (sgrowth)**:

    Follows Lakonishok et al. (1994). $sgrowth = SALE/SALE_{-12}$. Sales growth is the percent change in net sales over turnover (Compustat item SALE).

28. **Share Volume (shvol)**:

    Follows Datar et al. (1998). $shvol = \frac{1}{3}\sum_{i=1}^{3} volume_{t-i}/shrout_t$. Average number of shares traded over the previous three months scaled by shares outstanding. Rebalanced monthly.

29. **Size (size)**:

    Follows Fama and French (1993). $size = ME_{Jun}$. We use the CRSP end of June price times shares outstanding.

30. **Short-term Reversal (strev)**:

    Follows Jegadeesh (1990). $strev = r_{t-1}$. Return in the previous month. Rebalanced monthly.

31. **Standardized Unexpected Earnings (sue)**:

    Follows Foster et al. (1984). $sue = \frac{IBQ - IBQ_{-12}}{\sigma_{IBQ_{-24}:IBQ_{-3}}}$, where IBQ is income before extraordinary items (Rebalanced quarterly), and $\sigma_{IBQ_{-24}:IBQ_{-3}}$ is the standard deviation of IBQ in the past two years skipping the most recent quarter. Earnings surprises are measured by Standardized Unexpected Earnings (SUE), which is the change in the most recently announced quarterly earnings per share from its value announced four quarters ago divided by the standard deviation of this change in quarterly earnings over the prior eight quarters. Rebalanced monthly.

32. **Value (value)**:

    Follows Fama and French (1993). $value = BE/ME$. At the end of June of each year, we use book equity from the previous fiscal year and market equity from December of the previous year. Rebalanced annually.

33. **Value (valuem)**:

    Follows Asness et al. (2013). $valuem = BEQ_{-3}/ME_{-1}$. Book-to-market ratio using the most up-to-date prices and book equity (appropriately lagged). Rebalanced monthly.

34. **Gross Profitability (prof)**:

    Follows Novy-Marx (2013). $prof = GP/AT$, where GP is gross profits and AT is total assets. Rebalanced annually.

35. **Value-Profitability (valprof)**:

    Follows Novy-Marx (2013). $valprof = rank(value) + rank(prof)$. Sum of ranks in univariate sorts on book-to-market and profitability. Annual book-to-market and profitability values are used for the entire year. Rebalanced monthly.

36. **Piotroski's F-score (F-score)**:

    Follows Piotroski (2000). $F{-}score = 1_{IB>0} + 1_{\Delta ROA>0} + 1_{CFO>0} + 1_{CFO>IB} + 1_{\Delta DTA<0|DLTT=0|DLTT_{-12}=0}$ $1_{\Delta ATL>0} + 1_{EqIss \leq 0} + 1_{\Delta GM>0} + 1_{\Delta ATO>0}$, where IB is income before extraordinary items, ROA is income before extraordinary items scaled by lagged total assets, CFO is cash flow from operations, DTA is total long-term debt scaled by total assets, $DLTT$ is total long-term debt, ATL is total current assets scaled by total current liabilities, $EqIss$ is the difference between sales of common stock and purchases of common stock recorded on the cash flow statement, GM equals one minus the ratio of cost of goods sold and total revenues, and ATO equals total revenues, scaled by total assets. Rebalanced annualy.

37. **Debt Issuance (debtiss)**:

    Follows Spiess and Affleck-Graves (1999). $debtiss = 1_{DLTISS<=0}$. Binary variable equal to one if long-term debt issuance indicated in statement of cash flow. Updated annually.

38. **Share Repurchases (repurch)**:

    Follows Ikenberry et al. (1995). $repurch = 1_{PRSTKC>0}$. Binary variable equal to one if repurchase of common or preferred shares indicated in statement of cash flow. Updated annually.

39. **Dividend Yield (divp)**:

    Follows Naranjo et al. (1998). $divp = Div/ME_{Dec}$. Dividend scaled by price. Both are measured in December of the year t-1 or t-2 (for returns in months prior to July). Rebalanced annually.

40. **Cash flow duration (dur)**:

    Follows Giglio et al. (2021a). $dur = \sum_t PV_0(tÖCF_t)/P_0$. Present value of expected cashflows. Cashflows' components (from clean surplus identity, ROE and book equity growth) are forecasted using AR(1). Sums are discounted using a constant discount rate. Rebalanced monthly.

41. **Leverage (lev)**:

    Follows Bhandari (1988). $lev = (AT/ME)_{Dec}$. Market leverage is the ratio of total assets (Compustat item AT) over the market value of equity. Both are measured in December of the same year.

42. **Sales-to-Price (sp)**:

    Follows Barbee et al. (1996). $sp = SALE/ME_{Dec}$. Total revenues divided by stock price. Rebalanced annually.

43. **Value-Momentum-Profitability (valmomprof)**:

    Follows Novy-Marx (2013). $valmomprof = rank(B/M) + rank(Prof) + rank(Mom)$. Sum of ranks in univariate sorts on book-to-market, profitability, and momentum. Annual book-to-market and profitability values are used for the entire year. Rebalanced monthly.

44. **Short Interest (shortint)**:

    Follows Dechow et al. (1998). $shortint = SharesShorted/Shrout$. Rebalanced monthly.

45. **Share Issuance (monthly) (nissm)**:

    Follows Pontiff and Woodgate (2008). $nissm = shrout_{t-1}/shrout_{t-13}$, where $shrout$ is the number of shares outstanding. Change in real number of shares outstanding from $t-13$ to $t-1$. Excludes changes in shares due to stock dividends and splits, and companies with no changes in $shrout$.

46. **Return on Market Equity (rome)**:

    Follows Chen et al. (2011). $rome = IBQ/ME_{-4}$, where IBQ is income before extraordinary items (Rebalanced quarterly), and ME is market value of equity. Rebalanced monthly.

47. **Idiosyncratic Volatility (ivol)**:

    Follows Ang et al. (2006). $ivol = std(r_{i,t} - \beta_{m,i}R_{m,t} - \beta_{smb,i}SMB_t - \beta_{hml,i}HML_t)$. The standard deviation of the residual from firm-level regression of daily stock returns on the daily innovations of the Fama and French three-factor model using the estimation window of three months. Lagged one month. Rebalanced monthly.

48. **Beta Arbitrage (betaarb)**:

    Follows Cooper et al. (2008). $betaarb = \beta_{t-60:t-1}$. Beta with respect to the CRSP equal-weighted return index. Estimated over the past 60 months (minimum 36 months) using daily data and lagged one month. Rebalanced monthly.

49. **Firm Age (age)**:

    Follows Barry and Brown (1984). $age = log(1 + \text{number of months since listing})$. The number of months that a firm has been listed in the CRSP database. Rebalanced monthly.

B.4 Robustness check

We put in this section additional figures (B.12, B.13, B.14, B.15) concerning the robustness case scenario for the Fama-French 25 ME/BM-sorted portfolios and the fifty anomaly portfolios. For robustness purposes, we replace the first k linear factors directly by the nonlinear principal components in the risk factors instead of their mimicking portfolios. And price a set of portfolios containing n factors where we replace the first k linear principal components by k mimicking portfolios. Moreover, we let the LARS-EN algorithm adds the factors starting by the model with no risk factors instead of starting by the model with our k mimicking portfolios as risk factors. The figures confirm the results presented in the section 3.3. We checked the robustness of the mimicking portfolios (nonlinear) factors are always in the optimal model giving the highest R^2_{oos}. Our hybrid factors models outperform the linear models.

B.5 Least Angle Regression

1. Initialize $\hat{\lambda}^{(0)} = 0$, $\mathcal{A} = argmax_j|\Sigma'_j\mu|$, $\nabla\hat{\lambda}^{(0)}_{\mathcal{A}} = -sign(\Sigma'_{\mathcal{A}}\mu)$,$\nabla\hat{\lambda}^{(0)}_{I} = 0$, $n = 0$.
2. While $\mathcal{I} \neq \emptyset$ do ;
3. $\delta_j = \min^{+}_{j\in\mathcal{A}} -\frac{\hat{\lambda}^{(n)}}{\nabla\hat{\lambda}^{(n)}_j}$
4. $\delta_i = \min^{+}_{i\in\mathcal{I}} \left\{ \frac{(\Sigma_i+\Sigma_j)'(\mu-X\hat{\lambda}^{(n)})}{(\Sigma_i+\Sigma_j)'(\Sigma\nabla\hat{\lambda}^{(n)})}, \frac{(\Sigma_i-\Sigma_j)'(\mu-\Sigma\hat{\lambda}^{(n)})}{(\Sigma_i-\Sigma_j)'(\Sigma\nabla\hat{\lambda}^{(n)})} \right\}$ where j is any index in $\mathcal{A}$.
5. $\delta = \min(\delta_j, \delta_i)$
6. if $\delta = \delta_j$ then move j from $\mathcal{A}$ to $\mathcal{I}$ else move i from $\mathcal{I}$ to $\mathcal{A}$.
7. $\hat{\lambda}^{(n+1)} = \hat{\lambda}^{(n)} + \delta\nabla\hat{\lambda}^{(n)}$
8. $\nabla\hat{\lambda}^{(n+1)}_{\mathcal{A}} = -\frac{1}{2}\left(\Sigma_{\mathcal{A}} + \gamma_2 I\right)^{-1}.sign(\hat{\lambda}^{(n+1)}_{\mathcal{A}})$
9. Update the value of n=n+1
10. end while
11. Output the series of coefficients $\Lambda = (\hat{\lambda}^{(0)}, \hat{\lambda}^{(1)}, ..., \hat{\lambda}^{(k)})$

B.6 Nonlinear principal components estimation

We normalize each linear factor to have 0 mean and 1 standard deviation LF0=(lf_{01},...,lf_{0k}) and set a grid on the standardized data lf_m, $m \in \{1...ng\}^k$ where

$$lf_{mi} \in min(lf_{0i}) : \frac{max(lf_{0i}) - min(lf_{0i})}{ng - 1} : max(lf_{0i}), i = 1, ..., k$$

The estimation of the density function $g(lf_m)$ is done by kernel smoothing. Then the convex function C is computed via gradient descent algorithm using

$$C_{n+1}(lf_m) = C_n(lf_m) + \tau(g(lf_m) - \Phi(\frac{\partial C_n(lf_m)}{\partial lf_m})det(\frac{\partial^2 C_n(lf_m)}{\partial lf_m \partial lf'_m}) \tag{B.1}$$

All the derivatives are computed using centered finite differences :

$$T_j(lf_m) \approx \frac{\partial C_n(lf)}{\partial lf}_j = \frac{C_n(lf_{m+\Delta_j}) - C_n(lf_{m-\Delta_j})}{2 * step}, \quad j = 1, 2, ..., k$$

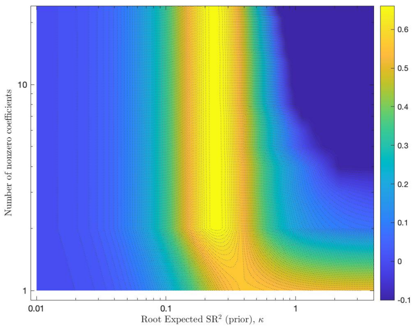
and

$$\frac{\partial^2 C_n(lf_m)}{\partial lf_i \partial lf'_j} \approx \frac{C_n(lf_{m+\Delta_j+\Delta_i}) - C_n(lf_{m-\Delta_j+\Delta_i}) - C_n(lf_{m-\Delta_i+\Delta_j}) + C_n(lf_{m-\Delta_j-\Delta_i})}{||lf_{m+\Delta_i} - lf_{m-\Delta_i}||||lf_{m+\Delta_j} - lf_{m-\Delta_j}||}$$

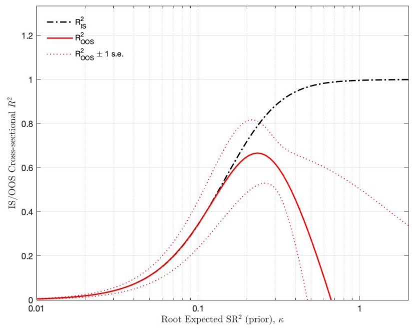
For any boundary points, we use an appropriate noncentered finite differences version that is second-order accurate. Let us denote C^* the optimal convex function and by $x^*_m = T(lf_m)$ the transformed data. The nonlinear principal components are obtained by diagonalizing the matrix $\overline{J}$ defined by :

$$\overline{J} = \sum_{m \in \{1...ng\}^k} \Phi(x^*_m) lnJ(lf_m) \prod_{j=1}^{d} \frac{||x^*_{m+\Delta_j} - x^*_{m-\Delta_j}||}{2}$$

where $J(lf) = \frac{\partial^2 C^*(lf)}{\partial lf \partial lf'}$. The eigenvectors of $\overline{J}$ associated to the k highest eigenvalues : $e_1...e_k$. Finally, we interpolate the Brenier map to have the full nonlinear transformation of the original data $T(LF_1, LF_2, ..., LF_k)$. Therefore, the i^{th} nonlinear factor is $NLF_i = T(LF_1, LF_2, ..., LF_k)e_i$.



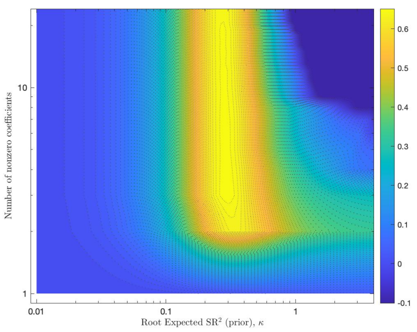
(a) Dual penalty



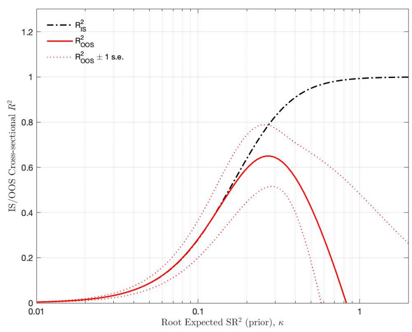
(b) L2 penalty

Figure B.12: Hybrid FF25P using 2 nonlinear factors +23 linear factors.

In the left panel, we plot in a color map the out-of-sample cross-sectional R^2 (R^2_{oos}) -calculated using 3-fold cross-validation- of the regression of the expected returns on the covariance matrix (risk factors) under the Elastic-Net penalty. In the right panel, we plot the R^2_{oos} (solid red) -calculated using 3-fold cross-validation- and the in-sample cross-sectional R^2_{is} (dashed black) of the regression of the expected returns on the covariance matrix (risk factors) under the Ridge penalty ($\gamma_1 = 0$). The confidence interval of the R^2_{oos}, i.e. $R^2_{oos} \pm 1s.e.$ is drawn with dotted lines.



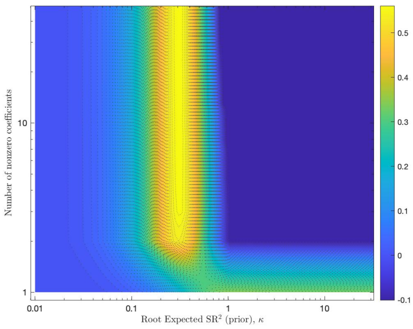
(a) Dual penalty



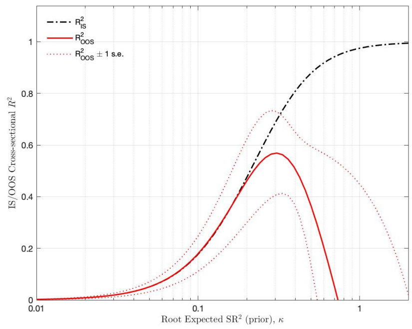
(b) L2 penalty

Figure B.13: Hybrid FF25P using 3 nonlinear factors +22 linear factors.

In the left panel, we plot in a color map the out-of-sample cross-sectional R^2 (R^2_{oos}) -calculated using 3-fold cross-validation- of the regression of the expected returns on the covariance matrix (risk factors) under the Elastic-Net penalty. In the right panel, we plot the R^2_{oos} (solid red) -calculated using 3-fold cross-validation- and the in-sample cross-sectional R^2_{is} (dashed black) of the regression of the expected returns on the covariance matrix (risk factors) under the Ridge penalty ($\gamma_1 = 0$). The confidence interval of the R^2_{oos}, i.e. $R^2_{oos} \pm 1s.e.$ is drawn with dotted lines.



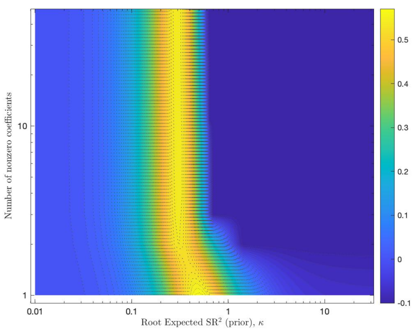
(a) Dual penalty



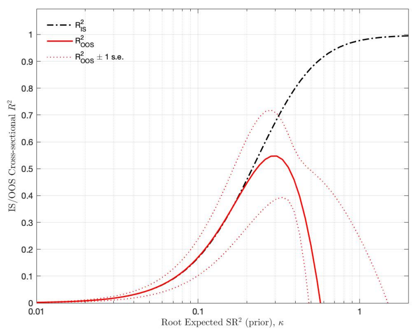
(b) L2 penalty

Figure B.14: Hybrid 50 anomaly portfolios using 2 nonlinear factors +48 linear factors.

In the left panel, we plot in a color map the out-of-sample cross-sectional R^2 (R^2_{oos}) -calculated using 3-fold cross-validation- of the regression of the expected returns on the covariance matrix (risk factors) under the Elastic-Net penalty. In the right panel, we plot the R^2_{oos} (solid red) -calculated using 3-fold cross-validation- and the in-sample cross-sectional R^2_{is} (dashed black) of the regression of the expected returns on the covariance matrix (risk factors) under the Ridge penalty ($\gamma_1 = 0$). The confidence interval of the R^2_{oos}, i.e. $R^2_{oos} \pm 1s.e.$ is drawn with dotted lines.



(a) Dual penalty



(b) L2 penalty

Figure B.15: Hybrid 50 anomaly portfolios using 3 nonlinear factors +47 linear factors.

In the left panel, we plot in a color map the out-of-sample cross-sectional R^2 (R^2_{oos}) -calculated using 3-fold cross-validation- of the regression of the expected returns on the covariance matrix (risk factors) under the Elastic-Net penalty. In the right panel, we plot the R^2_{oos} (solid red) -calculated using 3-fold cross-validation- and the in-sample cross-sectional R^2_{is} (dashed black) of the regression of the expected returns on the covariance matrix (risk factors) under the Ridge penalty ($\gamma_1 = 0$). The confidence interval of the R^2_{oos}, i.e. $R^2_{oos} \pm 1s.e.$ is drawn with dotted lines.

Appendix C

Appendix to Chapter 3

C.1 Tables

Table C.1: Mean return of deciles in %

This table presents the mean returns of deciles' anomaly portfolio. We use value-weighted returns for each anomaly-based portfolios and compute the average over January, 1978 - December 2019. d1 stands for the first decile, d2 for the second decile, ..., d10 for the last decile.

	d1	d2	d3	d4	d5	d6	d7	d8	d9	d10
size	1.00	1.16	1.20	1.11	1.02	1.21	0.85	1.05	1.06	0.93
value	1.12	1.36	1.08	1.09	1.29	1.14	0.84	1.09	1.15	1.06
prof	1.14	0.83	1.02	1.12	1.03	1.17	0.38	1.16	1.24	1.02
valprof	1.18	1.02	1.10	1.15	1.04	1.16	0.88	1.32	1.24	1.02
nissa	1.15	0.95	0.94	1.18	1.13	1.11	1.00	0.90	1.25	1.28
accruals	1.18	1.06	1.02	1.23	1.10	1.16	1.04	0.91	1.02	1.32
growth	1.14	1.06	1.10	0.89	1.09	1.08	0.97	0.92	0.39	1.57
aturnover	1.20	1.06	1.11	0.91	1.17	0.96	1.03	1.07	1.09	1.59
gmargins	1.13	1.14	1.03	1.15	0.80	1.10	1.07	1.00	1.28	0.76
divp	1.05	1.07	0.95	1.02	1.14	1.41	1.18	1.06	1.10	0.87
divg	1.00	1.27	1.08	1.20	1.03	0.90	1.21	1.11	1.25	0.94
dur	1.11	1.18	1.10	1.03	1.05	0.87	1.47	1.12	1.16	1.02
ep	1.13	0.93	1.12	1.10	1.01	1.06	0.90	1.13	1.10	1.14

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Table C.1 – continued from previous page

	d1	d2	d3	d4	d5	d6	d7	d8	d9	d10
cfp	1.02	1.11	0.98	1.16	1.02	0.92	1.09	1.35	1.10	1.13
noa	1.14	1.09	0.95	1.09	1.07	1.12	1.15	0.57	1.13	1.18
inv	1.11	1.08	1.12	1.21	1.14	1.31	1.08	0.86	1.09	1.24
invcap	1.08	1.06	1.13	1.05	1.02	1.16	1.10	0.97	0.98	1.31
igrowth	1.07	1.08	1.09	1.13	1.13	1.05	1.23	0.88	0.92	1.60
sgrowth	1.08	1.07	1.19	1.02	0.90	1.26	1.06	0.95	0.97	0.75
lev	1.27	1.17	1.20	1.09	0.98	1.19	1.20	0.98	1.10	1.00
roaa	0.85	1.24	1.14	1.09	0.95	1.01	1.19	1.12	1.16	1.02
roea	0.85	1.14	1.13	1.14	1.06	1.15	1.36	1.11	1.14	1.08
sp	0.93	0.76	1.22	1.04	0.97	1.06	1.14	1.10	1.15	1.06
gltnoa	0.97	1.01	1.28	1.02	1.09	1.09	1.08	1.28	1.08	1.12
mom	1.10	1.02	0.87	1.10	1.04	1.20	1.12	0.53	1.10	1.06
indmom	1.07	1.06	0.93	1.14	1.08	1.22	1.15	0.65	1.05	1.11
valmom	1.10	1.13	1.05	0.87	1.03	1.27	1.14	1.05	0.75	1.21
valmomprof	1.07	1.16	1.10	1.17	1.18	1.12	1.10	0.94	0.84	1.30
shortint	1.11	1.21	1.06	1.05	0.95	1.07	1.11	1.09	0.98	0.73
mom12	1.30	1.04	1.03	1.04	1.00	1.29	1.13	1.04	0.98	1.03
momrev	0.84	1.27	1.22	0.99	1.05	0.89	1.18	1.08	1.15	1.04
lrrev	0.95	1.23	1.16	1.12	1.13	1.10	1.20	1.33	1.04	1.21
valuem	0.85	0.93	1.14	1.11	1.17	1.09	1.05	1.34	1.05	1.11
nissm	1.02	0.95	1.33	1.12	1.11	1.18	1.05	1.55	1.05	1.10
sue	1.20	1.07	0.98	1.25	1.16	1.12	1.03	0.63	1.18	1.02
roe	1.17	1.04	1.14	1.12	1.26	0.91	0.98	0.79	1.44	1.05
rome	1.29	1.11	0.96	1.07	1.27	1.13	1.09	1.01	0.67	1.12
roa	1.33	1.00	1.11	1.05	1.38	1.19	0.99	1.02	0.76	1.02
strev	1.33	1.12	1.16	1.10	1.07	1.44	1.10	1.00	0.87	1.01

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Table C.1 – continued from previous page

	d1	d2	d3	d4	d5	d6	d7	d8	d9	d10
ivol	1.44	1.05	1.11	1.01	1.04	1.55	0.90	1.00	0.99	1.17
betaarb	0.72	0.98	1.02	1.12	1.00	1.01	1.35	1.15	1.03	1.03
season	0.93	1.11	1.15	1.21	1.17	1.03	1.23	1.07	1.14	1.02
indrrev	1.25	0.98	1.27	1.06	0.96	1.19	0.78	1.10	1.22	1.11
indrrevlv	1.15	1.00	1.23	1.13	1.07	1.21	0.91	1.18	1.35	0.98
indmomrev	1.05	1.09	0.68	1.18	1.06	1.22	1.27	0.76	1.46	1.17
ciss	1.04	1.09	0.98	0.98	1.10	1.04	1.09	0.86	1.35	1.02
price	1.04	1.05	1.05	1.03	1.12	1.07	1.13	1.02	0.63	1.01
shvol	1.14	1.21	0.81	1.03	1.08	0.96	1.03	1.07	0.85	0.96

Table C.2: R^2_{oos} of the predictive models

This table presents R^2_{oos} for diverse predictive model. Model 1 uses the best univariate decile predictors : bm, ltr, corpr, svar, Dpr, Dy. Model 2 uses the same set of predictors as model 1 but add an AR(1) term. Model 3 selects the best set of predictors among the fourteen available in a stepwise way. Model 4 uses only two limit-to-arbitrage predictors–namely VIX CBOE volatility index and the TED spread. Finally, Model 5=Model 2+ VIX+TED spread. We compute the R^2_{oos} as follow: the equation 3.4 is estimated using information from January 1978 to December 1992. Then the estimated coefficients are used to predict the return of the corresponding asset in January 1993. Next, the information on January 1993 is added to the training sample and reestimate the equation 3.4 using information from January 1978 to January 1993. The corresponding coefficients are used to predict the return in February 1993. The same exercise is performed until the end of the sample– that is December 2019. Lastly, the R^2_{oos} is computed using equation 3.7

	Split date: 1992m12			**Split date: 2004m12**		**Split date: 2004m12**		
Deciles	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 1***	**Model 2***	**Model 3***
size_p1	11.45	98.51	3.65	0.76	9.17	28.56	98.46	21.24
size_p2	17.42	87.46	12.41	4.25	21.58	32.47	92.48	32.92
size_p3	16.97	81.81	13.43	5.20	23.67	33.15	89.79	36.07
size_p4	16.16	77.58	12.58	4.85	18.66	27.86	85.94	30.85
size_p5	14.71	74.20	9.18	4.76	13.44	25.49	82.99	24.44
size_p6	14.53	68.31	11.19	3.92	13.67	24.03	79.62	26.52
size_p7	12.90	61.85	7.43	3.94	6.88	20.21	75.15	20.48
size_p8	14.57	59.86	11.27	4.91	7.96	22.46	74.19	25.37
size_p9	13.26	51.50	8.77	3.67	0.76	17.88	65.19	19.06
size_p10	16.42	46.08	12.47	9.34	10.95	27.87	67.45	28.87

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Table C.2 – continued from previous page

	Split date: 1992m12			Split date: 2004m12		Split date: 2004m12		
Deciles	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 1***	**Model 2***	**Model 3***
value_p1	8.78	82.50	2.94	-6.01	3.58	28.58	83.13	27.29
value_p2	9.50	84.73	3.27	-1.60	13.72	26.18	86.83	26.99
value_p3	3.58	80.32	-2.18	2.29	11.82	16.05	83.61	18.77
value_p4	16.31	79.41	5.29	5.91	15.61	29.22	87.98	22.03
value_p5	10.86	76.33	4.72	6.08	20.83	24.45	84.28	25.06
value_p6	16.14	72.71	9.51	4.50	23.84	28.09	83.02	26.26
value_p7	18.22	69.82	13.23	7.53	28.38	30.73	80.28	29.74
value_p8	18.46	64.39	14.38	5.05	22.74	29.05	77.16	26.35
value_p9	14.49	62.31	9.56	2.68	7.56	24.39	68.51	18.37
value_p10	19.59	56.86	14.88	3.89	12.35	24.66	60.17	22.83
prof_p1	10.75	70.67	6.90	-3.33	5.18	24.26	67.26	24.03
prof_p2	20.30	78.01	15.27	5.90	27.62	33.28	81.88	29.93
prof_p3	19.10	82.06	10.95	8.28	29.76	36.21	84.46	31.94
prof_p4	18.89	81.08	11.30	4.65	27.52	36.06	84.83	35.71
prof_p5	15.05	77.83	6.70	8.23	21.42	28.73	84.95	26.55
prof_p6	7.54	76.58	2.48	2.51	14.32	20.11	82.73	19.33
prof_p7	6.98	76.51	0.87	1.32	11.19	26.44	81.73	27.64
prof_p8	6.80	74.73	2.92	-1.87	-1.95	23.05	83.27	25.62
prof_p9	6.60	80.09	0.75	-5.02	-2.01	17.87	83.44	16.41
prof_p10	5.64	73.57	0.69	-8.35	-5.70	18.14	78.98	15.09
valprof_p1	13.95	85.87	4.68	1.75	22.47	35.96	86.63	31.63
valprof_p2	11.57	83.73	5.32	5.73	15.59	34.34	85.90	35.75
valprof_p3	9.67	79.71	4.03	0.82	22.16	25.71	84.51	24.92
valprof_p4	10.24	77.73	5.29	3.52	10.74	19.83	83.35	18.24
valprof_p5	10.59	85.05	5.12	-0.10	13.92	25.62	89.01	25.54
valprof_p6	12.13	77.54	6.64	-5.71	11.78	25.59	89.29	20.61
valprof_p7	12.87	70.89	6.58	-2.54	11.28	22.71	84.18	18.33
valprof_p8	10.35	65.19	7.12	1.27	-0.02	14.96	71.76	17.88
valprof_p9	14.15	66.61	11.02	2.14	2.32	21.69	73.31	22.34
valprof_p10	11.63	57.67	8.33	4.78	-2.28	13.83	61.70	16.57
nissa_p1	16.65	84.39	11.47	5.85	18.69	30.86	84.56	29.39
nissa_p2	16.18	80.68	13.96	3.97	18.28	35.16	83.92	36.32
nissa_p3	13.85	73.83	10.28	2.44	12.04	27.67	82.32	29.21
nissa_p4	12.81	82.49	8.78	0.90	16.67	23.07	82.24	24.75
nissa_p5	9.78	83.53	2.20	2.32	6.75	23.63	85.10	19.82
nissa_p6	7.98	77.67	0.74	4.32	8.63	22.63	88.53	19.18
nissa_p7	12.18	83.21	2.46	3.51	18.38	25.72	90.40	19.33

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Table C.2 – continued from previous page

	Split date: 1992m12			Split date: 2004m12		Split date: 2004m12		
Deciles	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 1***	**Model 2***	**Model 3***
nissa_p8	12.32	84.62	4.52	2.00	12.37	26.77	93.34	22.93
nissa_p9	11.39	80.70	6.17	2.74	11.34	26.75	90.76	22.66
nissa_p10	13.07	77.34	6.33	1.70	11.86	23.34	85.67	19.91
accruals_p1	12.42	68.41	6.27	3.39	-0.74	26.90	77.08	25.86
accruals_p2	13.81	79.82	8.28	-1.20	21.99	30.83	85.92	27.21
accruals_p3	9.33	81.09	5.97	-3.45	-0.11	19.90	83.77	22.68
accruals_p4	7.59	77.38	0.75	0.61	17.43	21.95	86.52	19.26
accruals_p5	6.67	82.27	-0.13	3.04	12.94	22.54	89.42	20.69
accruals_p6	12.68	81.06	6.99	2.80	12.92	27.84	88.72	26.68
accruals_p7	12.66	81.88	3.52	2.73	12.71	29.08	87.20	22.95
accruals_p8	11.98	78.96	5.46	4.36	23.60	28.56	87.53	25.69
accruals_p9	9.09	73.06	5.64	-1.88	9.94	29.80	81.91	30.71
accruals_p10	14.87	71.63	10.38	1.03	2.84	35.56	75.08	36.93
growth_p1	12.02	72.10	6.92	-3.76	12.08	29.63	76.69	29.76
growth_p2	8.28	71.55	4.97	-0.55	10.11	26.44	81.90	26.31
growth_p3	9.19	82.15	3.79	-3.65	8.25	23.46	84.69	25.12
growth_p4	8.63	83.92	1.56	-3.98	9.46	23.95	87.96	18.81
growth_p5	11.39	80.66	4.03	2.20	8.16	25.54	90.31	20.22
growth_p6	10.89	81.72	8.37	3.25	24.09	26.91	85.99	27.71
growth_p7	14.19	78.05	8.10	4.07	21.10	26.70	85.60	22.57
growth_p8	11.22	74.96	1.05	6.23	19.92	24.94	86.12	19.62
growth_p9	14.84	77.88	8.33	3.46	22.44	31.69	86.08	29.95
growth_p10	14.41	74.27	6.98	5.74	7.14	27.60	83.42	23.59
aturnover_p1	13.66	71.66	9.79	-0.50	10.88	32.02	82.18	27.15
aturnover_p2	7.21	77.66	0.33	1.26	17.58	29.23	85.51	27.79
aturnover_p3	12.82	82.34	6.47	2.47	2.83	30.84	87.07	30.16
aturnover_p4	9.19	80.24	1.55	-0.60	15.51	26.48	88.03	25.36
aturnover_p5	14.46	77.31	8.12	0.55	16.96	26.19	86.75	26.39
aturnover_p6	17.10	84.97	11.16	1.53	26.76	35.72	86.41	33.42
aturnover_p7	14.45	72.60	9.70	4.49	20.62	27.07	83.76	26.12
aturnover_p8	4.91	67.11	-0.27	2.90	10.95	13.77	74.78	14.78
aturnover_p9	9.28	66.06	7.76	-0.47	-2.16	15.43	73.18	20.69
aturnover_p10	1.17	65.00	-3.35	-4.41	-12.76	13.01	69.89	14.83
gmargins_p1	18.28	66.57	11.42	2.78	24.88	30.87	80.00	30.02
gmargins_p2	17.03	73.86	11.62	7.09	26.21	28.47	82.92	28.45
gmargins_p3	17.00	74.84	12.30	3.25	22.76	29.62	79.32	31.44
gmargins_p4	3.46	70.85	-4.38	5.81	4.75	13.42	72.98	15.06

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Table C.2 – continued from previous page

	Split date: 1992m12			Split date: 2004m12		Split date: 2004m12		
Deciles	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 1***	**Model 2***	**Model 3***
gmargins_p5	15.15	81.13	6.27	1.38	18.95	32.40	88.07	27.77
gmargins_p6	15.05	79.47	9.75	6.51	18.17	26.38	84.73	25.63
gmargins_p7	13.32	78.24	10.65	1.99	18.01	28.86	80.60	29.81
gmargins_p8	8.75	83.91	4.55	1.18	1.75	29.29	86.76	26.02
gmargins_p9	9.69	84.24	1.14	-1.62	0.58	28.54	90.29	24.13
gmargins_p10	8.83	82.00	3.96	-6.42	6.98	26.68	88.10	23.61
divp_p1	13.32	84.51	5.96	3.00	24.92	34.15	84.91	33.55
divp_p2	11.11	83.37	4.20	2.06	24.82	31.72	87.38	30.53
divp_p3	12.18	83.93	5.06	0.20	14.71	26.46	88.64	25.11
divp_p4	7.44	71.18	-0.41	3.21	13.54	23.98	86.86	19.58
divp_p5	8.50	66.32	1.04	4.36	21.65	18.87	81.59	14.74
divp_p6	4.51	71.96	-3.33	2.00	4.92	16.55	82.83	12.22
divp_p7	9.55	74.90	0.33	7.85	13.86	21.07	85.15	12.87
divp_p8	4.27	61.30	-5.99	3.54	-15.75	9.59	67.53	-0.63
divp_p9	8.74	51.84	1.91	3.10	8.25	15.50	65.82	8.13
divp_p10	7.90	38.07	-0.30	5.37	-13.46	9.30	41.08	-0.45
divg_p1	14.45	70.46	8.28	7.25	18.98	26.76	80.77	22.21
divg_p2	10.93	69.22	5.50	5.68	10.17	19.08	81.06	18.40
divg_p3	7.59	72.01	-1.60	6.18	14.15	15.37	77.29	9.73
divg_p4	13.76	75.09	5.61	6.11	30.28	28.25	84.22	21.77
divg_p5	5.20	69.01	-0.82	4.97	6.84	11.35	76.87	5.43
divg_p6	10.47	78.05	4.01	6.72	8.45	21.92	82.56	16.36
divg_p7	6.58	75.32	-1.03	-0.68	10.34	18.62	87.26	13.47
divg_p8	8.94	80.44	1.76	-0.44	-1.63	25.36	86.73	19.23
divg_p9	6.52	81.02	-1.47	-1.92	0.07	25.20	87.48	22.22
divg_p10	16.56	79.14	10.10	3.40	20.03	34.02	83.05	30.92
dur_p1	8.48	78.68	2.69	-8.25	-1.82	28.09	79.23	26.29
dur_p2	8.39	85.14	2.57	-1.12	11.82	27.80	89.36	27.79
dur_p3	5.05	77.49	1.06	-0.39	13.87	16.71	80.60	19.77
dur_p4	9.10	78.84	-0.78	4.76	7.64	24.75	86.37	21.46
dur_p5	9.97	74.06	2.47	4.35	8.37	15.34	82.30	12.01
dur_p6	13.82	73.64	8.54	5.37	15.67	27.13	83.05	27.80
dur_p7	14.02	74.32	8.78	5.56	13.15	22.09	83.58	20.89
dur_p8	18.09	66.10	10.90	5.47	25.31	30.36	75.19	27.61
dur_p9	24.28	70.77	20.62	3.41	18.58	34.52	76.44	35.33
dur_p10	18.83	55.45	16.54	4.49	10.43	25.42	58.09	26.92
ep_p1	16.04	63.98	10.90	1.29	9.93	32.58	73.73	32.87

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Table C.2 – continued from previous page

	Split date: 1992m12			Split date: 2004m12		Split date: 2004m12		
Deciles	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 1***	**Model 2***	**Model 3***
ep_p2	13.86	77.10	8.54	2.13	16.12	31.05	81.00	30.71
ep_p3	9.78	84.93	2.94	1.51	15.06	27.96	86.06	26.01
ep_p4	7.57	82.75	1.20	2.97	15.98	23.29	88.39	19.37
ep_p5	11.27	84.03	4.53	-1.05	12.89	27.79	91.35	23.78
ep_p6	8.33	78.36	1.76	3.36	13.45	20.98	87.97	17.69
ep_p7	10.33	77.61	3.99	4.34	10.97	24.97	89.98	23.17
ep_p8	11.59	75.26	4.53	5.16	5.13	19.32	82.96	13.23
ep_p9	18.36	74.85	12.56	8.93	15.72	29.19	84.37	24.46
ep_p10	14.33	67.17	9.13	5.98	7.59	17.18	71.41	15.88
cfp_p1	10.30	81.41	4.43	-0.59	9.97	28.70	80.69	27.34
cfp_p2	6.71	85.00	-0.74	-2.68	7.01	24.88	88.75	21.64
cfp_p3	7.61	86.12	-1.22	2.47	6.53	26.16	89.72	21.95
cfp_p4	12.56	78.74	3.66	3.68	19.63	25.65	90.15	21.32
cfp_p5	10.95	81.06	4.97	4.75	10.14	23.14	88.37	20.80
cfp_p6	9.56	75.73	0.84	6.10	1.78	19.01	82.83	12.56
cfp_p7	19.33	71.84	12.46	8.09	27.85	30.78	82.77	26.04
cfp_p8	13.68	66.62	6.73	7.42	20.00	22.06	83.22	16.92
cfp_p9	17.28	66.76	11.51	5.84	19.57	24.41	75.54	21.46
cfp_p10	21.44	64.63	17.96	5.12	18.13	31.46	71.72	32.09
noa_p1	14.87	73.60	10.41	2.52	7.56	33.30	75.62	34.57
noa_p2	10.78	74.17	8.33	2.01	14.85	23.92	83.10	23.94
noa_p3	13.43	76.47	9.90	0.10	12.82	27.98	82.39	25.18
noa_p4	12.03	76.09	3.65	0.73	9.43	34.89	82.84	27.93
noa_p5	8.78	77.46	-0.42	-2.67	2.98	23.19	80.33	21.29
noa_p6	12.48	81.91	6.41	1.57	10.97	29.95	89.39	27.05
noa_p7	10.21	79.95	2.62	1.57	13.71	25.11	86.44	21.34
noa_p8	13.52	80.05	7.67	2.86	24.84	29.65	88.34	29.20
noa_p9	10.56	76.90	5.37	-0.22	-0.89	27.21	85.08	27.59
noa_p10	11.01	71.60	8.64	-1.54	3.37	25.63	79.97	27.54
inv_p1	16.92	70.31	10.87	3.88	24.32	31.73	74.39	31.67
inv_p2	9.12	76.82	4.67	-4.00	-9.72	23.05	79.05	23.95
inv_p3	5.67	73.58	-0.29	-3.57	-26.29	16.23	66.99	15.35
inv_p4	12.13	81.21	6.36	-2.00	15.41	31.03	83.33	27.10
inv_p5	13.18	83.82	10.13	1.73	24.63	28.92	86.40	29.38
inv_p6	15.21	80.05	9.77	1.82	28.68	30.19	87.37	25.56
inv_p7	11.44	82.87	5.48	3.89	8.23	28.21	90.46	25.81
inv_p8	11.92	82.95	4.28	0.92	7.85	24.81	87.74	22.70

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Table C.2 – continued from previous page

	Split date: 1992m12			Split date: 2004m12		Split date: 2004m12		
Deciles	Model 1	Model 2	Model 3	Model 4	Model 5	Model 1*	Model 2*	Model 3*
inv__p9	10.95	81.03	2.07	0.59	10.57	24.04	88.38	19.06
inv__p10	13.34	76.63	5.40	7.64	18.20	27.07	83.13	24.68
invcap__p1	10.95	63.73	7.46	-5.36	-8.90	28.75	66.53	28.24
invcap__p2	11.76	75.11	8.94	-1.77	9.67	30.87	83.52	34.09
invcap__p3	12.19	83.21	6.86	-1.40	24.57	29.33	87.67	28.86
invcap__p4	13.70	83.82	4.43	4.34	16.43	31.21	90.55	26.49
invcap__p5	8.40	78.21	-0.26	-0.62	5.74	22.08	87.27	20.29
invcap__p6	9.29	76.50	1.47	2.45	12.57	19.76	84.32	18.48
invcap__p7	6.34	72.21	-2.07	5.52	16.99	18.29	83.31	11.66
invcap__p8	9.42	73.42	4.30	0.72	19.36	22.98	79.79	18.99
invcap__p9	15.68	69.53	10.94	2.44	17.59	28.25	80.05	24.79
invcap__p10	17.30	61.81	12.66	8.85	26.63	26.41	74.62	23.51
igrowth__p1	13.64	69.92	8.67	1.86	10.34	29.99	78.85	30.06
igrowth__p2	15.08	73.16	9.90	-2.26	19.32	31.34	76.83	32.38
igrowth__p3	9.99	82.40	2.98	0.90	11.95	26.27	88.52	24.23
igrowth__p4	10.86	77.47	4.51	-1.50	16.34	24.85	85.02	23.73
igrowth__p5	13.88	83.47	9.28	3.30	19.65	31.00	89.36	29.22
igrowth__p6	8.55	81.31	3.68	3.43	11.47	23.91	89.39	20.34
igrowth__p7	4.79	82.82	-2.89	0.32	-0.16	19.56	85.02	17.11
igrowth__p8	13.27	81.40	5.96	1.36	15.45	25.35	87.26	22.36
igrowth__p9	13.62	74.91	9.65	2.99	25.99	33.26	84.07	35.21
igrowth__p10	10.67	67.24	5.96	3.46	4.34	23.55	76.60	25.58
sgrowth__p1	12.42	70.90	8.31	-3.00	11.27	29.31	73.39	30.03
sgrowth__p2	9.09	68.85	4.36	0.33	13.81	25.68	80.86	26.50
sgrowth__p3	9.97	81.02	6.19	-0.77	5.21	21.01	86.38	23.64
sgrowth__p4	11.96	83.38	5.78	-3.27	-1.65	28.14	88.34	23.16
sgrowth__p5	8.67	81.22	5.45	0.80	15.70	25.36	85.37	23.82
sgrowth__p6	7.23	81.32	3.89	0.02	14.08	18.96	83.98	19.33
sgrowth__p7	8.92	75.17	1.55	6.37	19.56	23.72	85.03	19.52
sgrowth__p8	14.08	70.89	4.96	2.60	23.27	29.78	79.87	23.98
sgrowth__p9	17.36	78.53	11.18	5.43	22.35	32.85	83.65	32.14
sgrowth__p10	17.01	73.99	10.74	7.17	12.52	33.21	80.88	31.08
lev__p1	9.00	81.44	5.14	-5.73	2.57	28.38	84.00	27.17
lev__p2	5.04	82.06	-3.59	3.07	14.59	19.57	85.71	15.34
lev__p3	7.24	82.91	-0.01	1.90	13.57	21.66	89.50	21.40
lev__p4	13.08	80.86	5.38	0.16	15.85	28.41	87.61	24.14
lev__p5	15.63	75.19	7.60	5.39	28.96	30.69	83.54	26.94

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Table C.2 – continued from previous page

	Split date: 1992m12			Split date: 2004m12		Split date: 2004m12		
Deciles	Model 1	Model 2	Model 3	Model 4	Model 5	Model 1*	Model 2*	Model 3*
lev_p6	14.41	75.16	7.70	7.48	20.60	26.39	84.80	23.33
lev_p7	19.94	74.64	15.81	3.43	20.67	34.33	83.01	32.56
lev_p8	16.20	72.77	9.39	5.97	12.73	27.13	79.82	20.50
lev_p9	8.39	70.70	2.87	6.09	-6.40	17.52	76.24	13.59
lev_p10	10.60	60.42	4.46	6.35	3.40	14.08	61.13	7.19
roaa_p1	14.30	64.09	11.77	-0.77	0.25	29.50	71.46	30.72
roaa_p2	20.52	77.63	10.90	8.55	17.53	29.35	77.16	20.49
roaa_p3	5.86	71.25	-0.57	5.29	-7.96	12.02	72.28	6.62
roaa_p4	12.54	83.48	5.76	4.04	11.83	25.78	85.21	21.57
roaa_p5	15.00	77.94	9.86	5.57	21.42	31.03	88.17	29.33
roaa_p6	14.21	80.19	7.82	7.66	11.80	27.73	88.62	27.08
roaa_p7	15.64	82.86	6.53	7.51	27.93	29.38	89.09	23.39
roaa_p8	9.99	83.89	3.33	2.75	19.67	25.64	90.66	25.12
roaa_p9	7.55	86.11	-0.89	0.22	12.43	28.58	90.15	24.86
roaa_p10	8.38	81.38	4.33	-8.46	0.57	24.82	86.88	23.91
roea_p1	16.56	66.13	12.10	0.76	5.65	32.82	73.47	32.00
roea_p2	18.89	81.40	14.34	9.07	11.31	33.40	85.31	33.54
roea_p3	20.11	80.10	15.39	5.42	26.97	34.64	85.45	32.39
roea_p4	12.89	76.27	5.55	9.80	29.53	29.61	83.69	29.05
roea_p5	9.25	77.79	1.07	9.25	13.63	20.50	87.77	14.93
roea_p6	14.90	85.46	7.85	7.40	12.38	27.04	87.11	20.26
roea_p7	14.24	86.96	6.20	4.03	17.54	27.21	90.21	22.35
roea_p8	11.59	91.05	6.25	2.84	16.18	27.07	92.93	25.56
roea_p9	7.53	91.69	3.15	-2.49	4.87	22.94	93.05	21.77
roea_p10	9.36	84.72	2.07	-6.11	-1.44	25.79	88.16	23.62
sp_p1	10.81	84.81	4.79	-4.62	4.41	30.26	86.13	29.62
sp_p2	6.95	88.45	3.52	2.43	8.81	25.83	91.55	23.86
sp_p3	8.58	85.72	2.40	5.29	7.03	19.55	89.25	15.75
sp_p4	13.15	85.07	6.31	2.93	13.65	23.33	89.71	19.32
sp_p5	16.70	76.56	10.25	4.12	22.45	27.62	85.66	25.65
sp_p6	17.92	77.39	9.80	8.26	20.64	30.38	89.79	25.89
sp_p7	19.62	75.17	13.73	7.50	24.48	28.80	82.07	25.61
sp_p8	12.82	71.19	7.81	5.44	9.60	19.08	76.47	22.15
sp_p9	13.56	64.86	9.30	7.72	4.92	18.13	70.98	21.19
sp_p10	21.12	67.08	16.78	6.76	12.74	27.53	70.58	28.48
gltnoa_p1	15.34	78.94	10.20	0.07	6.96	30.15	86.32	31.10
gltnoa_p2	16.97	83.09	11.22	0.89	9.89	28.87	88.63	27.55

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Table C.2 – continued from previous page

	Split date: 1992m12			Split date: 2004m12		Split date: 2004m12		
Deciles	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 1***	**Model 2***	**Model 3***
gltnoa_p3	14.21	82.55	5.48	1.87	12.12	30.83	84.34	29.38
gltnoa_p4	11.56	78.33	7.34	4.47	20.67	24.48	84.89	24.04
gltnoa_p5	7.03	74.82	2.09	2.33	13.59	22.38	87.42	17.71
gltnoa_p6	10.50	81.54	3.87	2.45	0.48	24.67	88.62	22.49
gltnoa_p7	14.82	81.68	6.58	5.40	26.71	30.62	89.43	25.25
gltnoa_p8	11.02	78.56	6.15	2.95	15.52	24.43	91.52	22.65
gltnoa_p9	16.14	82.24	9.80	0.67	26.34	34.64	89.97	31.53
gltnoa_p10	8.48	78.31	3.29	0.73	9.92	29.72	84.26	30.79
mom_p1	15.13	65.32	12.22	-1.66	-11.77	28.81	65.32	28.34
mom_p2	14.34	73.25	9.82	-3.89	-9.45	27.07	73.28	26.90
mom_p3	10.91	75.22	5.74	-1.95	-2.50	22.10	77.71	19.15
mom_p4	9.43	80.45	3.57	0.38	-6.13	20.06	83.74	17.27
mom_p5	10.44	81.15	6.96	-4.70	3.81	23.20	87.32	23.88
mom_p6	7.78	80.08	4.10	-1.67	7.07	20.75	89.55	18.94
mom_p7	10.59	79.51	3.61	2.27	17.60	22.07	88.29	16.72
mom_p8	7.21	79.75	1.69	6.71	15.68	18.05	85.30	17.41
mom_p9	8.81	73.02	2.42	9.38	23.35	21.87	78.44	19.30
mom_p10	7.56	50.69	2.54	4.65	2.68	16.81	59.29	15.68
indmom_p1	16.71	60.03	11.32	3.97	-6.23	32.12	62.08	27.91
indmom_p2	9.63	65.22	3.78	-5.21	-20.81	20.92	68.93	18.61
indmom_p3	19.38	72.66	14.82	2.31	27.94	36.67	80.34	36.12
indmom_p4	7.39	66.24	1.84	-0.56	6.62	21.50	79.79	17.84
indmom_p5	8.57	66.35	1.87	3.04	14.75	20.60	82.66	14.74
indmom_p6	9.17	71.20	3.13	-4.24	9.11	19.18	82.56	14.27
indmom_p7	13.63	68.00	7.41	8.23	17.57	25.41	72.30	22.15
indmom_p8	6.69	67.17	-0.83	5.49	12.04	16.08	74.94	11.28
indmom_p9	5.60	64.29	-0.07	0.15	1.60	14.89	73.79	11.63
indmom_p10	3.97	42.37	-2.71	3.54	-5.44	7.69	52.22	2.86
valmom_p1	10.28	72.19	6.20	-6.44	-17.88	28.98	74.86	31.34
valmom_p2	7.84	79.77	2.29	-6.02	4.70	20.28	83.14	19.09
valmom_p3	10.96	82.92	5.13	-4.49	13.27	24.75	87.10	21.92
valmom_p4	10.53	82.49	6.32	-0.11	15.94	25.68	87.82	25.89
valmom_p5	10.77	81.83	5.52	-0.29	18.53	22.09	87.15	21.61
valmom_p6	13.67	75.94	8.63	1.08	14.16	23.66	82.49	22.97
valmom_p7	12.75	62.89	7.91	-1.78	21.69	25.46	80.66	24.77
valmom_p8	15.85	60.38	7.33	7.07	15.56	23.91	74.53	19.68
valmom_p9	16.13	59.21	8.88	8.14	15.49	24.91	73.86	19.34

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Table C.2 – continued from previous page

	Split date: 1992m12			Split date: 2004m12		Split date: 2004m12		
Deciles	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 1***	**Model 2***	**Model 3***
valmom__p10	13.55	47.68	7.15	8.63	18.07	20.31	60.45	17.80
valmomprof__p1	13.11	77.08	6.98	0.24	1.70	33.46	78.51	32.29
valmomprof__p2	14.31	81.40	9.78	-2.94	6.35	29.49	82.30	29.94
valmomprof__p3	12.46	77.68	6.22	-1.79	14.81	24.82	82.78	23.28
valmomprof__p4	8.34	78.03	1.54	-1.33	16.00	20.54	84.83	17.68
valmomprof__p5	11.19	78.80	3.47	0.19	13.66	26.24	86.69	22.66
valmomprof__p6	11.57	73.36	4.83	0.75	12.55	21.17	83.82	14.36
valmomprof__p7	12.31	76.45	6.01	5.44	22.81	26.23	83.23	25.11
valmomprof__p8	9.35	65.45	2.13	4.12	11.86	19.23	76.98	15.65
valmomprof__p9	6.58	59.95	2.46	0.54	3.04	10.31	68.62	9.32
valmomprof__p10	9.37	46.46	5.01	2.03	3.91	16.55	66.01	15.26
shortint__p1	11.79	70.41	6.40	3.69	0.13	23.62	70.71	23.00
shortint__p2	14.77	79.45	8.12	5.27	13.88	26.11	82.70	22.80
shortint__p3	16.83	82.32	12.44	3.59	20.09	30.06	83.57	29.32
shortint__p4	14.98	82.16	10.74	5.14	18.47	28.31	86.39	27.66
shortint__p5	16.12	85.16	9.62	1.04	21.64	30.32	86.89	26.18
shortint__p6	16.05	85.03	10.50	5.20	20.07	28.23	88.86	28.12
shortint__p7	13.18	79.69	7.30	3.29	12.54	29.24	89.25	27.85
shortint__p8	12.11	78.81	4.32	3.32	23.29	28.41	89.59	24.31
shortint__p9	6.82	72.86	1.41	4.57	16.27	20.05	90.85	19.23
shortint__p10	14.65	73.75	8.10	11.94	17.56	24.23	81.15	16.64
mom12__p1	14.31	56.85	8.90	2.12	-0.25	22.38	57.76	17.39
mom12__p2	19.64	70.06	15.38	0.56	-1.36	32.45	72.69	29.40
mom12__p3	10.53	69.02	5.05	-0.86	-4.99	21.59	69.24	18.87
mom12__p4	14.73	76.66	7.22	0.60	1.55	27.35	81.97	23.19
mom12__p5	10.01	78.62	4.29	0.38	3.88	18.53	83.63	14.59
mom12__p6	9.48	79.04	5.81	3.32	15.29	19.80	87.90	22.17
mom12__p7	3.56	77.55	-0.12	1.55	6.56	10.29	86.57	13.46
mom12__p8	7.49	78.03	1.52	5.21	14.70	19.74	85.79	19.06
mom12__p9	9.55	74.24	3.55	10.09	26.12	24.75	78.80	24.08
mom12__p10	4.82	53.11	1.16	5.53	14.56	18.34	63.28	18.15
momrev__p1	12.41	67.99	6.76	4.82	24.66	33.89	75.21	32.11
momrev__p2	10.81	82.13	2.55	6.98	18.15	25.20	82.15	20.44
momrev__p3	11.84	80.26	3.07	3.80	18.16	24.98	90.39	19.99
momrev__p4	12.97	86.25	6.92	4.42	18.20	26.08	90.70	23.61
momrev__p5	10.06	83.99	0.77	3.17	11.93	20.51	87.80	12.89
momrev__p6	7.52	85.14	1.77	1.14	-3.26	20.77	88.54	18.93

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Table C.2 – continued from previous page

	Split date: 1992m12			Split date: 2004m12		Split date: 2004m12		
Deciles	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 1***	**Model 2***	**Model 3***
momrev_p7	9.37	78.88	4.34	-0.79	10.70	21.42	84.37	20.96
momrev_p8	7.38	73.54	3.11	-2.94	-7.89	17.92	78.54	14.46
momrev_p9	15.96	72.11	10.19	1.34	15.46	30.24	78.73	27.62
momrev_p10	15.70	60.32	11.83	3.86	9.93	29.37	71.22	29.94
lrrev_p1	12.66	76.81	5.16	-0.11	18.86	33.84	76.74	32.52
lrrev_p2	10.27	82.62	0.15	4.08	21.69	27.98	83.27	19.55
lrrev_p3	8.54	78.52	-1.04	1.92	16.40	23.98	85.67	18.49
lrrev_p4	9.72	81.02	2.07	4.24	24.06	25.68	88.89	21.62
lrrev_p5	12.06	77.87	8.41	3.52	17.72	26.00	88.59	26.49
lrrev_p6	5.94	75.42	-1.58	3.68	2.41	15.69	84.66	10.76
lrrev_p7	12.56	76.76	9.74	4.80	7.89	20.27	84.36	19.67
lrrev_p8	13.61	71.09	10.52	4.45	18.08	21.59	80.39	22.05
lrrev_p9	14.89	71.49	11.00	0.84	14.48	19.73	75.81	18.81
lrrev_p10	15.52	58.03	13.95	2.31	15.99	21.05	62.58	23.17
valuem_p1	5.77	76.56	-0.01	-5.75	11.37	25.16	79.02	23.09
valuem_p2	4.24	84.07	-3.30	-1.92	2.05	18.99	85.51	18.13
valuem_p3	8.67	85.13	1.14	4.24	15.99	23.54	87.79	23.52
valuem_p4	13.83	81.47	6.92	6.59	16.99	32.28	87.66	31.53
valuem_p5	14.02	81.07	5.67	8.43	16.76	29.85	89.83	27.27
valuem_p6	15.02	74.06	10.83	6.52	12.41	28.35	83.76	28.12
valuem_p7	15.58	74.27	11.82	3.84	13.86	26.56	81.01	26.73
valuem_p8	17.73	69.79	14.74	4.11	20.04	31.61	77.17	29.56
valuem_p9	15.16	57.67	13.92	-3.42	-12.50	28.40	67.76	28.86
valuem_p10	16.45	51.94	12.11	0.92	-18.14	21.26	54.03	16.77
nissm_p1	19.76	80.00	14.69	7.67	20.71	32.46	80.40	29.33
nissm_p2	16.15	78.92	14.01	5.29	11.47	30.94	87.77	32.23
nissm_p3	11.60	79.66	9.28	0.68	-8.03	24.21	81.48	26.66
nissm_p4	10.78	81.30	2.61	1.92	17.36	24.97	82.89	20.13
nissm_p5	12.30	81.40	4.54	-0.47	16.69	26.37	85.11	21.95
nissm_p6	8.75	79.12	1.45	0.65	14.12	25.04	86.52	23.54
nissm_p7	11.17	78.31	3.17	3.46	18.69	25.62	91.61	23.14
nissm_p8	7.43	86.82	0.25	1.34	11.03	22.79	91.98	21.05
nissm_p9	11.75	83.11	2.66	4.49	12.97	26.58	91.72	18.56
nissm_p10	14.70	76.43	7.27	4.74	15.31	31.18	87.49	27.86
sue_p1	13.38	69.83	9.24	4.13	1.44	24.26	70.92	20.52
sue_p2	7.21	69.64	-0.70	3.08	-24.70	11.31	72.56	5.42
sue_p3	13.44	66.62	4.53	7.70	6.31	22.78	70.34	13.66

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Table C.2 – continued from previous page

	Split date: 1992m12			Split date: 2004m12		Split date: 2004m12		
Deciles	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 1⋆**	**Model 2⋆**	**Model 3⋆**
sue_p4	14.60	76.00	9.54	6.27	18.36	23.45	82.33	19.56
sue_p5	13.06	76.04	6.17	-1.77	14.82	27.20	80.20	20.70
sue_p6	2.15	75.02	-4.14	2.70	9.82	12.81	80.84	7.71
sue_p7	9.14	77.97	7.95	-2.03	11.82	20.31	83.32	20.09
sue_p8	8.05	77.82	3.43	-0.70	17.96	22.51	83.27	22.46
sue_p9	1.65	76.64	-1.97	1.60	11.42	17.53	80.62	15.74
sue_p10	12.41	76.00	6.91	1.44	18.63	33.34	80.78	32.21
roe_p1	21.90	67.28	18.07	6.70	26.46	40.50	78.25	36.88
roe_p2	21.00	80.58	15.06	5.28	5.37	34.54	82.84	31.43
roe_p3	11.06	78.06	5.40	1.36	-6.90	18.19	79.49	16.96
roe_p4	14.66	76.85	9.00	3.35	-2.59	22.63	82.50	17.25
roe_p5	13.54	83.03	7.75	6.76	7.82	26.46	86.38	24.04
roe_p6	13.83	86.00	8.59	8.66	24.61	30.25	88.41	29.26
roe_p7	11.73	84.51	4.05	5.37	17.13	23.07	88.72	17.68
roe_p8	7.99	85.22	4.33	0.37	20.09	25.20	88.58	27.43
roe_p9	8.77	86.98	2.16	-0.69	11.15	23.83	88.10	21.94
roe_p10	5.46	81.15	-0.80	-3.57	8.58	21.82	87.69	18.27
rome_p1	23.04	68.32	19.37	6.93	23.14	39.12	75.95	37.96
rome_p2	17.24	75.28	13.08	1.86	10.90	33.89	83.10	33.87
rome_p3	10.70	82.47	5.72	-0.18	7.75	23.68	81.10	23.31
rome_p4	13.34	85.55	6.96	1.88	17.68	28.95	90.23	26.00
rome_p5	11.71	83.72	3.04	1.72	4.50	30.57	90.29	25.85
rome_p6	6.40	81.14	0.78	1.49	0.42	20.14	92.17	17.69
rome_p7	6.24	78.59	1.24	6.09	21.00	21.76	86.76	17.93
rome_p8	8.71	75.85	6.31	6.04	14.30	21.98	89.12	21.94
rome_p9	9.93	69.21	6.48	2.76	8.00	16.50	77.24	16.34
rome_p10	15.63	67.95	10.85	4.20	19.70	23.44	72.45	23.60
roa_p1	18.33	63.57	16.34	4.38	14.63	35.44	76.01	35.65
roa_p2	24.79	80.07	18.69	8.20	27.70	36.91	80.44	31.71
roa_p3	7.15	69.79	1.29	3.25	-20.85	10.86	66.66	4.14
roa_p4	10.84	80.39	6.09	5.02	6.99	21.27	80.75	16.54
roa_p5	10.02	80.86	1.96	0.36	4.25	20.81	85.87	15.30
roa_p6	14.08	81.79	5.49	3.53	16.40	25.34	85.86	22.39
roa_p7	16.28	82.87	7.42	6.10	25.19	31.09	87.78	27.36
roa_p8	6.33	81.16	1.52	3.58	19.50	23.68	88.39	25.01
roa_p9	11.56	85.32	6.83	-2.04	17.75	31.12	89.95	29.25
roa_p10	5.24	77.05	0.21	-4.17	10.59	22.33	83.20	20.72

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Table C.2 – continued from previous page

	Split date: 1992m12			Split date: 2004m12		Split date: 2004m12		
Deciles	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 1***	**Model 2***	**Model 3***
strev_p1	8.73	59.85	6.32	-0.63	4.41	20.70	66.75	20.63
strev_p2	2.71	74.91	-1.54	-6.63	0.00	10.51	75.52	7.45
strev_p3	10.79	83.01	7.32	-1.13	18.69	28.71	86.46	26.65
strev_p4	9.28	85.56	2.46	-0.67	9.36	23.77	88.70	20.70
strev_p5	13.68	85.65	7.51	4.81	19.89	26.97	88.43	25.18
strev_p6	10.62	84.88	3.95	3.94	1.39	22.32	88.42	18.75
strev_p7	11.48	83.28	4.99	4.36	17.88	25.70	84.51	23.70
strev_p8	17.78	79.47	13.62	6.36	25.28	31.74	83.33	30.44
strev_p9	15.68	75.46	11.42	6.39	7.81	28.06	80.61	27.44
strev_p10	17.35	67.53	9.30	4.32	9.15	29.27	73.32	22.63
ivol_p1	15.98	57.99	12.13	1.13	6.04	30.63	67.67	29.36
ivol_p2	15.28	69.78	11.21	0.04	8.60	33.24	75.54	34.49
ivol_p3	15.30	77.09	10.24	1.63	15.52	27.30	81.87	26.93
ivol_p4	17.66	80.53	11.91	-0.26	16.56	32.88	84.06	32.28
ivol_p5	19.29	83.98	13.41	3.59	15.78	35.02	84.50	34.98
ivol_p6	12.42	82.35	2.41	6.24	15.53	22.58	88.20	15.76
ivol_p7	12.89	84.14	5.38	5.04	12.69	26.55	89.97	22.65
ivol_p8	9.83	84.48	4.41	1.47	18.01	24.71	90.49	23.30
ivol_p9	5.96	82.06	-0.19	-0.49	14.92	23.03	91.99	19.19
ivol_p10	6.89	73.60	1.03	2.63	8.63	16.16	85.01	9.67
betaarb_p1	19.08	80.74	15.24	-0.07	22.49	32.52	78.46	32.68
betaarb_p2	20.95	76.83	12.33	6.24	25.81	31.38	80.34	25.54
betaarb_p3	21.29	77.85	13.60	6.29	31.63	32.33	83.44	26.83
betaarb_p4	13.40	73.12	5.96	4.71	13.05	22.29	78.55	16.26
betaarb_p5	11.94	68.55	5.25	4.54	19.21	22.50	78.71	18.97
betaarb_p6	11.91	74.89	8.46	5.88	20.41	26.20	85.68	27.18
betaarb_p7	8.91	60.87	2.66	8.09	20.71	17.28	81.13	14.35
betaarb_p8	8.53	61.65	2.17	5.57	17.70	16.93	76.91	14.47
betaarb_p9	7.10	45.68	3.34	7.49	16.48	14.73	71.26	10.12
betaarb_p10	3.45	34.83	1.90	5.90	2.30	4.83	51.18	6.28
season_p1	12.61	64.34	10.01	1.11	19.98	21.84	75.98	27.14
season_p2	13.26	76.47	10.36	3.94	22.89	20.36	82.84	20.76
season_p3	10.62	79.61	5.49	3.15	4.74	21.58	85.04	20.51
season_p4	13.48	83.40	6.81	7.92	20.01	29.83	87.25	27.07
season_p5	11.90	85.09	5.51	1.73	-1.33	21.69	88.38	17.40
season_p6	7.87	84.86	0.36	2.80	5.13	17.43	87.60	14.38
season_p7	10.68	83.87	1.24	1.96	10.24	25.21	88.52	18.81

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Table C.2 – continued from previous page

	Split date: 1992m12			Split date: 2004m12		Split date: 2004m12		
Deciles	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 1***	**Model 2***	**Model 3***
season_p8	7.32	85.71	0.82	5.38	11.81	21.43	87.44	16.87
season_p9	11.40	82.30	2.89	3.40	15.99	29.02	84.67	24.62
season_p10	14.71	76.98	8.04	0.12	15.97	32.46	78.06	30.40
indrrev_p1	9.28	60.69	6.64	-0.30	6.95	21.50	71.62	23.30
indrrev_p2	10.18	78.77	4.55	-3.10	10.02	23.66	81.80	22.63
indrrev_p3	7.52	89.01	1.28	-0.14	5.36	18.95	88.64	17.28
indrrev_p4	15.33	90.79	8.40	4.96	13.97	31.07	93.29	26.66
indrrev_p5	12.03	88.62	6.76	-0.48	15.23	28.84	90.66	26.68
indrrev_p6	13.32	86.53	5.70	0.38	16.42	24.68	91.96	20.10
indrrev_p7	13.66	87.32	7.64	2.87	11.80	25.97	88.84	22.99
indrrev_p8	14.86	83.10	8.40	8.25	21.11	29.99	84.69	27.62
indrrev_p9	15.15	80.33	11.35	4.69	0.11	28.56	83.44	29.45
indrrev_p10	17.63	72.74	13.88	1.39	8.33	32.20	79.04	34.02
indrrevlv_p1	8.79	71.60	4.17	4.48	7.34	13.58	78.83	11.49
indrrevlv_p2	6.38	80.17	1.71	-6.58	-5.84	16.97	81.81	15.76
indrrevlv_p3	1.97	76.92	-3.68	4.35	3.51	13.09	86.23	5.77
indrrevlv_p4	10.04	74.39	2.44	2.63	9.27	22.69	85.40	14.88
indrrevlv_p5	9.00	73.47	2.24	0.05	18.68	23.03	82.02	18.33
indrrevlv_p6	11.80	81.09	5.30	2.47	15.63	25.12	87.91	19.75
indrrevlv_p7	12.05	73.81	6.86	4.66	20.02	22.91	86.16	18.83
indrrevlv_p8	7.05	75.94	-0.62	1.59	10.02	21.10	85.01	16.30
indrrevlv_p9	7.96	73.87	4.32	0.13	7.43	17.69	80.77	19.52
indrrevlv_p10	13.28	74.32	6.27	7.19	25.46	28.21	81.50	24.13
indmomrev_p1	11.21	66.61	4.34	0.84	4.38	27.69	76.00	22.21
indmomrev_p2	10.20	70.08	3.09	-3.48	3.99	23.74	79.49	19.40
indmomrev_p3	3.92	70.53	-0.06	-3.45	2.64	12.01	85.55	11.06
indmomrev_p4	8.78	74.13	2.03	2.69	-0.42	23.02	85.59	17.70
indmomrev_p5	4.82	74.52	-1.08	3.51	5.33	16.64	83.92	13.24
indmomrev_p6	8.70	76.13	3.80	6.38	4.38	18.60	84.34	14.41
indmomrev_p7	11.37	79.09	8.10	3.12	22.08	21.75	84.68	20.79
indmomrev_p8	7.27	74.92	2.78	5.03	18.05	18.49	81.64	14.99
indmomrev_p9	9.73	73.50	3.70	2.65	16.46	20.06	80.53	15.89
indmomrev_p10	5.38	69.56	-0.84	1.26	9.16	17.14	78.71	13.87
ciss_p1	12.46	82.70	7.99	4.28	5.57	28.86	84.91	30.14
ciss_p2	9.65	83.26	1.99	4.07	18.00	25.19	86.70	22.01
ciss_p3	10.67	83.37	6.03	0.98	10.34	24.50	84.61	24.72
ciss_p4	13.44	83.09	9.06	3.76	22.19	30.86	88.22	31.89

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Table C.2 – continued from previous page

	Split date: 1992m12			Split date: 2004m12		Split date: 2004m12		
Deciles	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 1***	**Model 2***	**Model 3***
ciss_p5	8.78	80.83	4.33	1.86	3.46	20.09	85.84	20.65
ciss_p6	11.97	83.94	6.59	0.40	19.67	27.01	88.55	23.00
ciss_p7	9.81	83.51	2.01	4.05	18.37	24.08	89.53	20.12
ciss_p8	12.40	79.43	5.05	2.45	8.85	25.86	89.79	20.33
ciss_p9	7.07	78.81	0.00	-1.09	2.54	17.01	89.84	12.91
ciss_p10	21.20	78.55	13.23	10.70	7.25	31.40	87.62	27.11
price_p1	12.71	50.30	10.94	2.38	-24.24	20.58	61.31	23.13
price_p2	16.15	65.83	12.33	2.93	-4.53	23.95	71.39	23.65
price_p3	21.15	72.57	18.49	5.53	13.18	31.77	79.74	32.71
price_p4	13.21	74.53	10.19	1.09	-17.26	22.81	80.18	23.14
price_p5	16.04	80.52	10.18	1.05	10.59	30.91	86.81	27.60
price_p6	9.60	82.84	4.90	2.34	-12.78	19.99	88.40	17.59
price_p7	11.58	86.79	6.13	3.17	-5.36	25.52	91.43	23.56
price_p8	12.73	88.26	5.56	4.04	14.96	30.49	93.07	26.96
price_p9	10.90	91.81	3.49	-0.65	7.84	29.03	93.68	28.80
price_p10	10.06	84.91	3.09	2.47	20.22	24.60	86.43	22.81
shvol_p1	14.43	66.29	11.45	-1.86	14.96	31.41	75.47	31.36
shvol_p2	14.75	80.46	9.69	2.99	18.74	31.16	84.49	31.62
shvol_p3	16.11	85.72	8.29	7.24	17.87	32.07	87.61	30.18
shvol_p4	21.05	86.06	14.20	8.84	27.69	36.50	87.78	32.34
shvol_p5	8.20	83.45	1.63	5.39	10.89	18.76	86.68	17.52
shvol_p6	16.52	84.87	8.85	6.62	15.09	29.84	91.26	24.66
shvol_p7	10.29	79.46	3.83	4.91	13.31	25.39	89.38	22.03
shvol_p8	6.60	78.27	-0.74	-0.67	8.36	24.16	88.19	20.17
shvol_p9	4.32	67.96	-3.22	-1.41	12.21	16.75	84.16	13.81
shvol_p10	1.81	59.35	-3.87	5.74	-1.07	10.44	70.25	8.74

Table C.3: Trading strategies comparison

This table presents the performance of two trading rules. **Trading rule 1:** Go long the decile with the highest expected return and go short the decile with the lowest expected return. **Trading rule 2:** Go long the first (last) decile and go short the last (first) decile based on which extreme decile has the highest average return. The model 2 is adopted to do the forecasting and the strategy starts as of 1993m2. The statistics relative to the first trading rule are indexed by m while they are indexed by b for the second trading rule. For each rule, we present the mean return of the obtained long-short portfolios (μ), student test statistic for testing $H_0 : \mu = 0$, the terminal wealth of investing 1$ at the beginning of the forecasting period (tw), student test statistic for testing $H_0 : \mu_m = \mu_b$, and the breakeven transaction cost that equates the long leg mean returns of both strategies. Finally, the breakeven transaction costs (unadjusted, adjusted by the standard deviation) that equate the mean returns of the long positions of both strategies are provided. Each strategy starts in January 1993 and it holds until December 2019. The statistics are calculated using monthly information. See section 3.2.1 in the main text.

	L-S mean returns and tstats				Breakeven t-cost		Terminal wealth		T-stat
	μ_m(%)	t_m	μ_b(%)	t_b	no-sd(%)	with sd(%)	tw_m	tw_b	$H_0: \mu_m = \mu_b$
size	1.31	6.28	0.09	0.34	0.86	0.65	53.60	0.53	4.22
value	0.69	3.55	0.08	0.33	0.38	0.37	7.60	0.54	2.41
prof	0.63	3.70	0.39	2.18	0.40	0.38	6.57	0.23	4.13
valprof	0.85	4.62	0.42	2.00	0.61	0.64	12.87	0.20	4.54
nissa	0.79	4.21	0.63	3.57	0.58	0.67	10.81	0.11	5.51
accruals	1.30	6.20	0.37	1.94	0.89	1.02	51.89	0.25	5.90
growth	0.99	4.93	0.24	1.14	0.53	0.65	19.65	0.36	4.21
aturnover	0.26	1.44	0.35	1.70	0.34	0.35	1.94	0.26	2.23
gmargins	0.45	2.41	0.24	1.33	0.24	0.27	3.54	0.38	2.65
divp	1.06	4.27	0.21	0.68	0.78	0.89	22.17	0.31	3.23
divg	0.53	2.99	0.21	1.04	0.39	0.48	4.69	0.40	2.75
dur	0.59	2.49	0.15	0.52	0.49	0.46	4.99	0.41	2.00
ep	1.67	6.15	0.45	1.50	0.97	1.32	147.45	0.14	5.23
cfp	0.90	4.50	0.12	0.48	0.54	0.59	14.79	0.50	3.23
noa	0.97	4.99	0.74	3.68	0.88	0.94	18.89	0.07	6.12
inv	0.38	2.28	0.33	1.88	0.34	0.42	2.94	0.29	2.93
invcap	1.75	6.02	0.04	0.11	0.68	0.89	179.80	0.63	3.88
igrowth	0.88	4.24	0.24	1.37	0.54	0.71	13.70	0.40	4.14
sgrowth	1.09	5.05	0.15	0.65	0.62	0.75	26.24	1.23	3.03
lev	0.77	3.50	0.05	0.18	0.36	0.37	9.30	0.54	2.23
roaa	1.50	6.36	0.29	1.12	0.78	1.05	93.44	0.28	5.15
roea	1.43	6.46	0.28	1.01	0.64	0.83	75.63	0.27	4.85
sp	0.92	4.50	0.26	1.14	0.51	0.49	15.43	0.32	3.83
gltnoa	0.70	4.03	0.10	0.74	0.31	0.36	8.06	1.26	2.68
mom	1.96	6.18	0.14	0.33	0.87	1.01	322.50	0.28	4.04
indmom	0.68	2.05	0.38	0.96	0.56	0.65	5.11	0.13	2.06
valmom	0.90	3.47	0.23	0.76	0.61	0.66	12.91	0.30	2.84

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Table C.3 – continued from previous page

	L-S mean returns and tstats				Breakeven t-cost		Terminal wealth		T-stat
	$\mu_m(\%)$	t_m	$\mu_b(\%)$	t_b	no-sd(%)	with sd(%)	tw_m	tw_b	$H_0: \mu_m = \mu_b$
valmomprof	1.32	5.58	0.81	2.64	1.02	1.15	52.76	0.04	5.50
shortint	1.24	6.49	0.11	0.51	0.61	0.76	44.14	1.13	4.00
mom12	2.30	5.91	0.79	1.72	1.51	1.96	727.84	0.03	5.14
momrev	0.93	3.82	0.48	1.71	0.68	0.75	14.86	0.14	3.79
lrrev	1.33	5.43	0.08	0.29	0.81	0.80	52.41	0.50	3.76
valuem	1.42	4.70	0.06	0.17	0.65	0.44	60.48	0.35	3.11
nissm	0.79	4.10	0.52	2.42	0.58	0.73	10.61	0.15	4.55
sue	0.07	0.35	0.31	1.31	0.32	0.38	1.00	0.27	1.21
roe	1.41	5.81	0.59	1.94	0.89	1.25	68.51	0.09	5.13
rome	2.02	7.01	0.93	3.00	1.23	1.77	422.27	0.03	6.96
roa	1.29	4.81	0.44	1.56	0.85	1.13	43.77	0.15	4.44
strev	1.43	5.21	0.23	0.68	0.95	0.93	67.84	0.26	3.82
ivol	2.57	7.42	0.41	0.92	1.33	2.12	2027.37	0.09	5.24
betaarb	3.46	11.55	0.10	0.25	1.78	2.47	38330.12	0.34	7.33
season	0.82	4.58	0.45	2.03	0.66	0.75	11.83	0.18	4.45
indrrev	1.93	8.25	0.40	1.55	1.32	1.38	362.99	0.19	6.68
indrrevlv	0.84	4.86	0.63	3.53	0.77	0.73	12.88	0.11	5.91
indmomrev	0.47	2.79	0.52	2.46	0.40	0.42	3.95	0.15	3.67
ciss	0.86	4.98	0.42	2.38	0.56	0.65	13.60	0.22	5.19
price	1.66	4.73	0.16	0.38	0.91	1.27	108.22	0.27	3.35
shvol	2.39	8.22	0.12	0.33	1.10	1.51	1365.24	0.72	4.84

Table C.4: Deciles inclusion in the long position (%)

This table presents the frequencies of inclusion of each decile in the long position of the deciles-based-strategy proposed in this paper. The frequencies can be nonnull for all the deciles because there is a possibility to go long any decile based on its expected return. If one considers the usual trading rule to form the long-short portfolios, the frequency of d1 or d10 would be 100% and the other zero as one goes long either the first decile or the last decile. **Trading rule:** The strategy here consists of going long the decile with the highest expected return. The model 2 is adopted to do the forecasting and the strategy starts as of 1993m2

	d1	d2	d3	d4	d5	d6	d7	d8	d9	d10
size	18.58	6.81	3.10	3.72	0.31	7.12	0.31	3.72	18.58	37.77
value	15.17	0.62	10.53	0.62	3.72	3.10	6.19	16.72	2.48	40.87
prof	21.98	4.95	4.95	4.95	6.50	2.17	18.89	2.79	0.31	32.51
valprof	14.24	2.17	0.62	2.79	6.19	14.86	13.93	5.26	1.55	38.39

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Table C.4 – continued from previous page

	d1	d2	d3	d4	d5	d6	d7	d8	d9	d10
nissa	4.02	6.50	26.93	3.10	5.26	1.24	0.62	0.31	8.05	43.96
accruals	0.31	0.93	0.00	3.10	2.79	11.15	23.84	0.00	14.55	43.34
growth	11.46	15.48	4.64	8.98	0.00	10.53	13.62	2.79	11.15	21.36
aturnover	19.20	4.33	4.02	10.84	0.62	11.46	8.05	0.00	38.70	2.79
gmargins	10.84	10.84	16.72	14.86	8.36	1.55	14.24	3.41	0.00	19.20
divp	34.37	1.55	1.86	0.00	0.31	8.67	4.95	2.48	9.91	35.91
divg	5.57	11.76	2.48	5.26	23.22	1.24	8.67	2.48	11.15	28.17
dur	11.76	2.48	6.50	1.55	4.33	0.31	13.62	1.86	3.41	54.18
ep	37.77	5.88	2.79	1.55	0.62	0.62	10.84	13.62	2.17	24.15
cfp	20.43	2.17	0.31	0.62	3.41	5.57	1.24	11.76	22.60	31.89
noa	0.62	18.58	13.93	0.31	2.48	3.72	7.12	6.19	14.86	32.20
inv	14.55	3.10	8.67	2.79	12.69	13.93	2.17	4.95	14.55	22.60
invcap	41.18	6.19	0.31	0.93	2.17	5.57	4.95	7.74	13.31	17.65
igrowth	13.62	15.48	1.24	2.17	0.62	15.17	8.05	7.43	21.05	15.17
sgrowth	38.70	2.79	3.10	1.86	5.57	21.67	8.05	4.02	10.22	4.02
lev	9.91	0.62	4.02	19.20	2.17	1.24	10.84	7.43	2.79	41.80
roaa	26.01	30.03	7.12	7.43	12.69	0.31	4.02	8.05	0.93	3.41
roea	40.87	3.41	20.74	3.41	8.98	2.48	2.79	2.48	1.24	13.62
sp	9.29	10.22	5.26	4.95	4.64	0.31	11.76	1.86	8.36	43.34
gltnoa	21.05	2.79	4.02	27.24	6.50	6.81	0.93	1.24	0.62	28.79
mom	25.08	1.55	3.10	3.72	2.48	8.98	7.43	0.00	0.31	47.37
indmom	25.39	4.33	0.31	0.00	0.62	4.02	11.15	3.10	8.05	43.03
valmom	18.58	8.05	2.17	1.24	0.31	7.12	19.50	2.17	5.57	35.29
valmomprof	15.48	2.79	0.31	4.33	8.36	0.31	0.93	0.00	14.86	52.63
shortint	35.29	2.48	8.98	7.12	19.81	0.62	1.24	2.79	7.12	14.55
mom12	17.96	5.57	1.55	4.95	2.17	0.00	6.50	8.36	1.86	51.08
momrev	6.19	4.95	3.72	0.31	8.05	7.12	0.93	13.93	3.41	51.39
lrrev	14.55	0.31	0.62	2.79	13.31	4.64	0.00	3.72	18.89	41.18
valuem	17.96	6.81	1.55	3.41	5.26	0.00	7.43	6.81	19.20	31.58
nissm	7.12	6.19	22.91	6.50	3.10	1.55	4.02	4.33	12.07	32.20
sue	11.46	0.00	1.86	19.50	7.12	4.95	2.17	2.79	14.86	35.29
roe	29.10	7.12	3.41	0.93	6.50	0.93	22.29	3.10	2.79	23.84
rome	22.91	0.93	11.46	0.00	0.31	3.41	2.17	11.46	6.19	41.18
roa	25.39	14.86	13.62	4.64	11.15	0.00	5.88	3.10	8.67	12.69
strev	6.19	1.24	6.81	5.57	2.79	8.67	11.76	12.69	11.76	32.51
ivol	15.48	28.17	6.19	0.31	10.84	3.10	0.31	0.31	2.79	32.51
betaarb	51.39	0.31	1.55	0.31	1.55	0.93	0.00	0.93	18.58	24.46
season	0.93	0.00	4.95	0.31	19.50	1.24	2.79	0.62	4.95	64.71

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Table C.4 – continued from previous page

	d1	d2	d3	d4	d5	d6	d7	d8	d9	d10
indrrev	1.24	0.00	0.31	2.17	4.95	14.86	10.53	13.62	11.76	40.56
indrrevlv	0.00	0.00	2.17	4.33	5.57	2.48	12.69	10.22	6.81	55.73
indmomrev	2.79	2.48	2.48	0.31	7.43	2.48	6.50	4.95	8.36	62.23
ciss	10.84	11.76	13.62	7.12	4.95	3.72	0.31	8.36	17.96	21.36
price	35.29	7.12	9.29	4.64	4.02	0.62	0.93	4.64	14.24	19.20
shvol	38.39	15.48	2.17	1.86	0.93	0.31	1.86	3.10	7.12	28.79

Table C.5: Deciles inclusion in the short position (%)

This table presents the frequencies of inclusion of each decile in the short position of the deciles-based-strategy proposed in this paper. The frequencies can be nonnull for all the deciles because there is a possibility to go short any decile based on its expected return. If one considers the usual trading rule to form the long-short portfolios, the frequency of d1 or d10 would be 100% and the other zero as one goes short either the first decile or the last decile. **Trading rule:** The strategy here consists of going short the decile with the lowest expected return. The model 2 is adopted to do the forecasting and the strategy starts as of 1993m2.

	d1	d2	d3	d4	d5	d6	d7	d8	d9	d10
size	44.89	3.10	3.72	0.00	6.19	2.79	3.10	4.02	9.91	22.29
value	40.25	2.48	0.62	6.50	0.62	3.10	2.17	8.98	27.55	7.74
prof	15.79	26.63	9.91	5.57	4.02	6.19	18.27	2.17	7.12	4.33
valprof	30.34	0.62	21.36	31.89	0.93	0.00	0.00	0.62	1.86	12.38
nissa	47.37	6.50	0.31	0.00	1.55	6.19	21.67	4.02	12.07	0.31
accruals	52.63	4.95	0.93	2.17	14.55	6.50	11.76	4.02	0.00	2.48
growth	43.03	5.57	0.00	8.67	2.48	14.24	22.60	0.62	0.00	2.79
aturnover	39.94	11.15	19.81	3.72	4.02	0.93	0.93	7.43	10.22	1.86
gmargins	19.20	6.81	0.62	7.12	0.00	23.22	8.05	4.02	26.32	4.64
divp	34.37	5.26	0.62	3.41	3.10	1.55	0.00	0.93	23.22	27.55
divg	32.51	2.79	0.62	2.48	24.15	8.98	1.24	6.81	0.62	19.81
dur	47.68	7.12	2.79	2.48	9.29	0.93	12.38	2.79	4.64	9.91
ep	28.48	14.86	0.62	14.24	4.64	14.86	0.00	8.05	13.62	0.62
cfp	32.20	6.19	12.69	5.26	2.48	1.24	12.69	8.05	12.07	7.12
noa	46.75	3.72	4.64	32.82	0.31	2.17	4.95	0.00	0.31	4.33
inv	34.06	20.12	0.31	6.19	8.67	25.08	4.33	0.31	0.62	0.31
invcap	35.60	2.48	9.91	0.00	1.86	0.00	9.29	16.41	3.72	20.74
igrowth	42.41	0.93	1.86	2.48	11.46	31.27	0.93	1.86	3.10	3.72
sgrowth	27.86	1.24	8.67	4.64	6.19	3.72	29.41	4.02	1.24	13.00
lev	30.03	14.55	4.95	0.00	4.64	13.00	2.79	13.00	1.86	15.17
roaa	34.67	2.17	4.02	1.24	30.03	7.74	4.64	0.93	13.00	1.55

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Table C.5 – continued from previous page

	d1	d2	d3	d4	d5	d6	d7	d8	d9	d10
roea	34.67	5.26	13.31	5.26	24.77	2.48	0.62	0.93	6.50	6.19
sp	33.44	34.98	3.10	0.31	0.31	4.33	0.00	2.79	7.74	13.00
gltnoa	8.67	17.96	6.50	18.58	17.34	2.17	2.17	2.79	1.55	22.29
mom	37.77	4.64	8.36	1.86	9.91	0.62	13.93	19.20	1.55	2.17
indmom	31.27	5.88	3.72	17.34	19.20	2.79	0.31	4.33	6.19	8.98
valmom	44.89	0.62	6.19	15.79	0.31	0.00	3.10	8.05	18.58	2.48
valmomprof	42.41	2.48	4.64	0.31	4.64	38.39	0.31	2.17	3.10	1.55
shortint	32.51	3.72	1.24	0.00	0.00	1.55	1.86	11.46	45.20	2.48
mom12	49.54	5.57	6.19	0.93	12.07	1.24	16.41	0.62	6.19	1.24
momrev	38.70	4.64	1.86	13.93	16.41	0.00	11.46	0.93	2.79	9.29
lrrev	26.01	7.74	17.96	13.31	5.26	3.41	8.05	1.24	0.93	16.10
valuem	25.39	0.62	2.79	1.24	1.55	2.48	0.00	34.67	2.17	29.10
nissm	42.11	9.91	1.55	0.31	0.62	0.31	21.98	8.98	13.93	0.31
sue	31.89	31.89	8.05	2.48	5.88	4.95	11.46	0.93	2.17	0.31
roe	42.41	1.86	0.93	16.72	27.55	4.95	0.00	0.93	0.62	4.02
rome	38.70	13.93	0.31	13.62	0.93	13.00	13.00	3.72	2.48	0.31
roa	41.18	3.10	2.79	0.31	28.79	9.29	3.72	4.02	0.93	5.88
strev	12.07	20.43	8.36	5.26	11.76	1.86	0.00	0.93	1.86	37.46
ivol	47.37	0.62	1.24	3.72	1.24	1.86	0.31	2.48	2.48	38.70
betaarb	33.44	4.64	2.48	1.55	4.33	2.17	0.62	9.29	7.74	33.75
season	26.01	33.75	13.62	0.31	0.00	7.43	0.62	10.53	0.00	7.74
indrrev	19.81	5.57	4.64	8.36	23.84	4.64	0.00	0.62	0.93	31.58
indrrevlv	58.82	1.55	12.69	3.72	13.93	1.55	0.00	0.62	0.31	6.81
indmomrev	30.65	32.51	27.24	1.24	1.24	2.79	1.86	1.86	0.31	0.31
ciss	47.06	3.41	1.24	0.00	0.31	4.02	11.15	15.17	0.31	17.34
price	43.03	3.41	3.10	0.00	1.24	9.60	5.88	3.41	1.55	28.79
shvol	33.44	0.00	4.95	2.48	1.55	7.12	0.93	7.74	8.36	33.44

Table C.6: Annualized Sharpe Ratio

This table presents the Sharpe Ratio –measuring the risk-adjusted performance of the deciles-based and benchmark strategies compared to the risk-free rate– of each anomalies considered in this paper. **Deciles-based strategy:** Go long the decile with the highest expected return and go short the decile with the lowest expected return. **Benchmark strategy:** Go long the first (last) decile and go short the last (first) decile based on which extreme decile has the highest average return. The model 2 is adopted to do the forecasting and the strategy starts as of 1993m2. The annualized Sharpe Ratio for each portfolio i is calculated using the following formula: $SR_i = \sqrt{12} \times \frac{E(r_i - r_f)}{\sigma_i}$. σ_i is the standard deviation of the strategy's return, $E(r_i - r_f)$ is the expected excess return of the portfolio i with respect to the risk-free rate. Column L stands for Long position, S for Short position, and L-S for Long-Short strategy.

	Deciles-based strategy			Benchmark strategy		
Anomalies	L	S	L-S	L	S	L-S
size	1.11	0.28	1.21	0.73	0.55	0.07
value	0.94	0.45	0.69	0.69	0.66	0.07
prof	0.87	0.42	0.73	0.59	0.90	0.42
valprof	0.97	0.35	0.90	0.48	0.76	0.38
nissa	0.87	0.24	0.80	0.38	0.97	0.69
accruals	1.04	0.17	1.18	0.38	0.55	0.38
growth	0.94	0.21	0.94	0.45	0.73	0.21
aturnover	0.62	0.48	0.28	0.38	0.73	0.31
gmargins	0.76	0.42	0.45	0.52	0.76	0.24
divp	1.14	0.31	0.83	0.48	0.59	0.14
divg	0.80	0.38	0.59	0.42	0.59	0.21
dur	0.87	0.52	0.48	0.59	0.55	0.10
ep	1.11	0.03	1.18	0.38	0.83	0.28
cfp	1.04	0.38	0.87	0.62	0.62	0.10
noa	0.90	0.24	0.97	0.28	0.69	0.69
inv	0.76	0.42	0.45	0.42	0.73	0.35
invcap	1.07	-0.03	1.14	0.48	0.76	0.03
igrowth	0.87	0.21	0.83	0.38	0.55	0.28
sgrowth	1.07	0.31	0.97	0.55	0.52	0.14
lev	0.94	0.35	0.66	0.66	0.52	0.03
roaa	0.97	0.00	1.21	0.35	0.80	0.21
roea	0.87	-0.03	1.25	0.35	0.87	0.21
sp	0.94	0.35	0.87	0.62	0.69	0.21
gltnoa	1.07	0.52	0.76	0.73	0.69	0.14
mom	1.00	0.00	1.18	0.48	0.73	0.07
indmom	0.73	0.38	0.38	0.38	0.73	0.17

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Table C.6 – continued from previous page

	Deciles-based strategy			Benchmark strategy		
Anomalies	L	S	L-S	L	S	L-S
valmom	1.00	0.45	0.66	0.55	0.80	0.14
valmomprof	1.11	0.24	1.07	0.38	0.94	0.52
shortint	0.94	0.07	1.25	0.42	0.45	0.10
mom12	0.94	-0.17	1.14	0.17	0.69	0.35
momrev	0.90	0.31	0.73	0.42	0.62	0.31
lrrev	1.11	0.31	1.04	0.62	0.55	0.07
valuem	0.76	0.10	0.90	0.66	0.42	0.03
nissm	0.90	0.24	0.80	0.35	0.90	0.45
sue	0.73	0.66	0.07	0.42	0.73	0.24
roe	0.87	0.00	1.11	0.21	0.90	0.38
rome	1.04	-0.21	1.35	0.17	0.94	0.59
roa	0.87	0.07	0.94	0.28	0.80	0.31
strev	0.97	0.07	1.00	0.38	0.38	0.14
ivol	1.11	-0.35	1.42	0.21	0.97	0.17
betaarb	1.63	-0.55	2.22	0.35	0.97	0.03
season	0.94	0.38	0.87	0.42	0.69	0.38
indrrev	1.21	0.00	1.59	0.38	0.48	0.31
indrrevlv	1.00	0.38	0.94	0.45	0.80	0.69
indmomrev	0.94	0.55	0.52	0.55	1.00	0.48
ciss	0.94	0.24	0.97	0.42	0.97	0.45
price	0.87	0.00	0.90	0.28	0.76	0.07
shvol	1.25	-0.24	1.59	0.42	0.80	0.07

Table C.7: Trading strategy - filter rule

This table presents the findings of the expected returns filter rule for the long (L), short (S) and long-short ($L-S$) positions. We compute the mean returns (μ), the Sharpe Ratio (SR), and the terminal wealth of investing 1$ at the beginning of the forecasting period – January 1993. **Expected returns filter rule strategy:** Go long any decile for which the expected return exceeds the average risk-free rate ($> \mu_{rf}$) and go short any decile for which the expected return is below the average risk-free rate ($< -\mu_{rf}$). If there is no decile exceeding or below the average risk-free rate, then the strategy suggests going long/short on the 1-month T-bill. The model 2 is adopted to do the forecasting and the strategy starts as of 1993m2. See section 3.2.1 in the main text for more details about the trading strategy.

Anomalies	$\mu_L(\%)$	SR_L	$\mu_L(\%)$	SR_L	$\mu_{L-S}(\%)$	SR_{L-S}	tw_L	tw_S
size	2.47	0.67	-1.21	-0.43	3.68	1.00	2009.95	0.02
value	2.16	0.81	-1.00	-0.47	3.16	1.09	827.08	0.03
prof	2.16	0.78	-1.09	-0.49	3.25	1.09	820.93	0.03

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Table C.7 – continued from previous page

Anomalies	$\mu_L(\%)$	SR_L	$\mu_L(\%)$	SR_L	$\mu_{L-S}(\%)$	SR_{L-S}	tw_L	tw_S
valprof	2.26	0.84	-1.07	-0.49	3.33	1.17	1137.20	0.03
nissa	2.22	0.82	-1.13	-0.50	3.35	1.15	1088.85	0.03
accruals	2.27	0.83	-1.18	-0.49	3.45	1.17	1176.11	0.02
growth	2.21	0.83	-1.14	-0.52	3.35	1.20	983.78	0.02
aturnover	2.12	0.74	-1.05	-0.49	3.17	1.04	759.13	0.03
gmargins	2.15	0.81	-1.08	-0.49	3.23	1.11	864.31	0.03
divp	2.08	0.79	-0.92	-0.38	3.00	0.97	594.98	0.05
divg	2.06	0.82	-1.01	-0.49	3.07	1.11	650.54	0.04
dur	2.25	0.78	-1.01	-0.44	3.26	1.01	1059.32	0.03
ep	2.32	0.84	-1.20	-0.49	3.52	1.19	1237.35	0.02
cfp	2.19	0.84	-1.04	-0.49	3.23	1.14	882.53	0.03
noa	2.19	0.79	-1.17	-0.49	3.36	1.09	938.28	0.02
inv	2.19	0.81	-1.18	-0.52	3.37	1.17	1016.88	0.02
invcap	2.21	0.81	-1.09	-0.49	3.30	1.17	806.93	0.03
igrowth	2.26	0.81	-1.16	-0.49	3.42	1.14	1156.14	0.02
sgrowth	2.26	0.85	-1.08	-0.48	3.34	1.17	1114.55	0.03
lev	2.20	0.81	-1.08	-0.49	3.28	1.11	947.12	0.03
roaa	2.27	0.79	-1.25	-0.50	3.52	1.13	1103.22	0.02
roea	2.28	0.83	-1.23	-0.50	3.51	1.17	1171.45	0.02
sp	2.25	0.82	-1.07	-0.47	3.32	1.11	1099.49	0.03
gltnoa	2.18	0.83	-1.07	-0.50	3.25	1.15	943.39	0.03
mom	2.37	0.74	-1.20	-0.51	3.57	1.13	1261.89	0.02
indmom	2.22	0.74	-1.10	-0.44	3.32	0.99	979.97	0.03
valmom	2.23	0.82	-1.09	-0.52	3.32	1.15	1012.05	0.03
valmomprof	2.25	0.77	-1.09	-0.51	3.34	1.15	1012.59	0.03
shortint	2.24	0.80	-1.13	-0.48	3.37	1.10	1015.83	0.02
mom12	2.34	0.70	-1.33	-0.47	3.67	1.03	1170.85	0.02
momrev	2.30	0.82	-1.12	-0.48	3.42	1.13	1233.94	0.03
lrrev	2.24	0.79	-1.07	-0.49	3.31	1.11	976.01	0.03
valuem	2.20	0.67	-1.09	-0.45	3.29	0.92	793.16	0.03
nissm	2.22	0.82	-1.13	-0.50	3.35	1.14	1052.40	0.03
sue	2.23	0.81	-1.12	-0.49	3.35	1.13	1090.30	0.02
roe	2.27	0.81	-1.28	-0.49	3.55	1.12	1171.53	0.02
rome	2.38	0.82	-1.33	-0.51	3.71	1.19	1401.16	0.02
roa	2.27	0.77	-1.27	-0.48	3.54	1.07	1121.00	0.02
strev	2.31	0.80	-1.28	-0.51	3.59	1.15	1298.84	0.02
ivol	2.53	0.73	-1.41	-0.44	3.94	1.05	1995.55	0.01
betaarb	2.26	0.75	-1.23	-0.49	3.49	1.14	680.84	0.03

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Table C.7 – continued from previous page

Anomalies	$\mu_L(\%)$	SR_L	$\mu_L(\%)$	SR_L	$\mu_{L-S}(\%)$	SR_{L-S}	tw_L	tw_S
season	2.19	0.81	-1.13	-0.50	3.32	1.15	945.55	0.02
indrrev	2.41	0.82	-1.27	-0.48	3.68	1.15	1622.68	0.02
indrrevlv	2.14	0.86	-0.95	-0.49	3.09	1.18	794.58	0.04
indmomrev	2.07	0.84	-0.89	-0.47	2.96	1.13	639.50	0.05
ciss	2.21	0.84	-1.13	-0.51	3.34	1.20	1008.01	0.03
price	2.49	0.71	-1.32	-0.38	3.81	0.94	1922.79	0.01
shvol	2.26	0.76	-1.23	-0.50	3.49	1.15	848.62	0.02

Table C.8: After-trading-cost returns: deciles-based strategy versus benchmark strategy (%)

This table presents the after-trading-cost performance of the proposed strategy versus the traditional long-short strategy based on the extreme deciles. We compute the weighted average trading cost of each anomaly for the long/short position, the after-trading-cost returns using the equations 3.10, 3.11, and 3.12. In the table, $tcost^i_{s,p}$, $R^a_{s,i}$, and $R^a_{s,i}$ denote the weighted average transaction cost for taking a position s (long or short) using the strategy s (m or b) in anomaly i, the gross annualized return for investing in anomaly i using strategy s (m or b), the net of transaction cost annualized return for investing in anomaly i using strategy s (m or b), respectively . As mentioned, m stands for deciles-based strategy, b for benchmark strategy. $p = L, S$ for long and short. **Deciles-based strategy (m):** Go long the decile with the highest expected return and go short the decile with the lowest expected return. **Benchmark strategy (b):** Go long the first (last) decile and go short the last (first) decile based on which extreme decile has the highest average return. The model 2 is adopted to do the forecasting and the strategy starts as of 1993m2. See section 3.2.1 in the main text for more details about the computation.

	Deciles-based strategy				Benchmark strategy			
Anomalies	$tcost_{m,L}$	$tcost_{m,S}$	$R^a_{m,i}$	$netR^a_{m,i}$	$tcost_{b,L}$	$tcost_{b,S}$	$R^a_{b,i}$	$netR^a_{b,i}$
size	1.55	2.19	15.72	11.98	0.80	3.50	1.08	-3.22
prof	2.01	1.92	7.56	3.63	1.95	2.70	4.68	0.03
nissa	1.55	1.55	9.48	6.37	1.60	1.50	7.56	4.46
accruals	1.82	2.15	15.60	11.63	2.05	2.60	4.44	-0.21
agrowth	1.82	2.01	11.88	8.05	1.80	2.60	2.88	-1.52
aturnover	2.01	2.13	3.12	-1.02	2.00	2.45	4.20	-0.25
gmargins	1.95	2.00	5.40	1.45	2.00	2.50	2.88	-1.62
noa	1.62	2.39	11.64	7.62	0.90	2.85	8.88	5.13
inv	1.90	2.12	4.56	0.54	1.85	2.65	3.96	-0.54
invcap	2.26	2.21	21.00	16.53	2.75	2.10	0.48	-4.37
igrowth	1.89	2.00	10.56	6.67	2.10	2.55	2.88	-1.77
sgrowth	1.87	1.83	13.08	9.38	2.25	2.05	1.80	-2.50
lev	1.27	1.24	9.24	6.73	1.40	1.30	0.60	-2.10
roaa	2.28	2.07	18.00	13.64	1.65	3.05	3.48	-1.22
sp	1.33	1.32	11.04	8.39	1.55	1.55	3.12	0.02

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Table C.8 – continued from previous page

	Deciles-based strategy				Benchmark strategy			
Anomalies	$tcost_{m,L}$	$tcost_{m,S}$	$R^a_{m,i}$	$netR^a_{m,i}$	$tcost_{b,L}$	$tcost_{b,S}$	$R^a_{b,i}$	$netR^a_{b,i}$
gltnoa	1.78	1.88	8.40	4.74	1.55	1.00	1.20	-1.35
mom	2.01	2.03	23.52	19.48	1.85	3.10	1.68	-3.27
indmom	1.75	1.74	8.16	4.67	1.85	1.85	4.56	0.86
mom12	1.88	2.32	27.60	23.40	1.65	3.30	9.48	4.53
momrev	1.69	2.00	11.16	7.47	1.80	2.90	5.76	1.06
lrrev	1.46	1.82	15.96	12.68	1.25	3.05	0.96	-3.34
nissm	1.64	1.61	9.48	6.23	1.50	1.60	6.24	3.14
sue	1.70	1.70	0.84	-2.56	1.70	1.75	3.72	0.27
roe	1.84	1.82	16.92	13.26	2.00	2.00	7.08	3.08
rome	0.73	0.74	24.24	22.77	0.70	0.90	11.16	9.56
strev	1.92	1.99	17.16	13.25	2.20	2.75	2.76	-2.19
season	1.50	1.70	9.84	6.64	1.80	2.45	5.40	1.15
indrrev	1.91	1.98	23.16	19.27	2.20	2.75	4.80	-0.15
ciss	1.65	1.39	10.32	7.28	1.90	1.05	5.04	2.09
price	1.46	2.18	19.92	16.29	0.75	3.50	1.92	-2.33
shvol	1.83	1.88	28.68	24.97	2.25	1.65	1.44	-2.46

Table C.9: R^2_{oos} of the predictive models using only past prices (%)

This table presents the R^2_{oos} of the predictive model using only past prices for all the deciles. We use two split dates: 1992m12, and 2004m12. We compute the out-of-sample R^2_{oos} using equation 3.7.

Deciles	1992m12	2004m12	Deciles	1992m12	2004m12
size_p1	-0.573	-0.534	mom_p1	-0.158	0.665
size_p2	0.051	0.323	mom_p2	-0.484	0.142
size_p3	0.024	0.193	mom_p3	-0.361	-0.517
size_p4	-0.216	-0.481	mom_p4	-0.336	-0.352
size_p5	-0.462	-0.929	mom_p5	-0.328	-0.257
size_p6	-1.029	-0.922	mom_p6	-0.499	-0.672
size_p7	-1.137	-1.73	mom_p7	-0.588	-0.54
size_p8	-0.597	-1.595	mom_p8	-0.305	-0.173
size_p9	-1.128	-1.574	mom_p9	-0.605	-0.357
size_p10	2.169	1.402	mom_p10	-0.418	-0.221
value_p1	-0.669	0.151	indmom_p1	-0.769	-1.009
value_p2	-0.364	-0.437	indmom_p2	-0.056	-0.143
value_p3	-0.316	-0.728	indmom_p3	-0.259	0.355

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Table C.9 – continued from previous page

Deciles	1992m12	2004m12	Deciles	1992m12	2004m12
value_p4	0.444	0.534	indmom_p4	-0.589	-0.35
value_p5	-0.599	-0.582	indmom_p5	-0.419	-0.969
value_p6	-0.771	-0.568	indmom_p6	-0.09	0.032
value_p7	-0.335	-0.303	indmom_p7	-0.353	-0.155
value_p8	-1.069	-0.428	indmom_p8	-0.348	-0.339
value_p9	-0.842	-0.775	indmom_p9	0.262	0.078
value_p10	1.115	1.28	indmom_p10	-0.919	-0.235
prof_p1	-0.184	0.137	valmom_p1	-0.867	-0.403
prof_p2	-0.738	-0.561	valmom_p2	-0.752	-0.851
prof_p3	-0.467	-0.4	valmom_p3	-0.55	-0.379
prof_p4	-0.572	-0.547	valmom_p4	-0.337	-0.338
prof_p5	-0.54	-0.46	valmom_p5	-0.322	0.123
prof_p6	-0.428	-0.498	valmom_p6	-0.603	-0.622
prof_p7	-0.767	-0.309	valmom_p7	-0.593	-0.543
prof_p8	-0.666	-0.427	valmom_p8	0.006	-0.392
prof_p9	-0.869	-1.039	valmom_p9	-0.311	-0.331
prof_p10	-0.675	0.588	valmom_p10	-0.405	-0.432
valprof_p1	0.499	0.921	valmomprof_p1	-0.556	-0.274
valprof_p2	-0.519	-0.011	valmomprof_p2	-0.524	-0.346
valprof_p3	-0.659	-0.477	valmomprof_p3	-0.583	-0.522
valprof_p4	-0.425	-0.121	valmomprof_p4	-0.447	-0.517
valprof_p5	-0.541	-0.47	valmomprof_p5	-0.427	-0.33
valprof_p6	-0.52	-0.551	valmomprof_p6	-0.298	0.301
valprof_p7	-0.52	-0.434	valmomprof_p7	-0.564	-0.407
valprof_p8	-0.33	-1.321	valmomprof_p8	-0.657	-0.385
valprof_p9	0.645	0.281	valmomprof_p9	-0.494	-0.317
valprof_p10	0.238	-1.224	valmomprof_p10	-0.712	-0.399
nissa_p1	0.916	1.081	shortint_p1	0.183	0.059
nissa_p2	0.071	1.065	shortint_p2	-0.132	-0.061
nissa_p3	-0.617	-0.467	shortint_p3	-0.343	-0.443
nissa_p4	-0.394	-0.388	shortint_p4	-0.083	0.004
nissa_p5	-0.238	-0.057	shortint_p5	-0.514	-0.559
nissa_p6	-0.559	-0.735	shortint_p6	-0.413	-0.478
nissa_p7	-0.443	-0.357	shortint_p7	-0.672	-0.931
nissa_p8	-0.315	-0.191	shortint_p8	0.426	0.558
nissa_p9	-0.448	-0.398	shortint_p9	-0.145	-0.493
nissa_p10	-0.491	-0.544	shortint_p10	-0.583	-0.579
accruals_p1	-1.143	0.019	mom12_p1	0.06	1.118

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Table C.9 – continued from previous page

Deciles	1992m12	2004m12	Deciles	1992m12	2004m12
accruals_p2	-0.725	-0.622	mom12_p2	-0.704	0.595
accruals_p3	-0.383	-0.983	mom12_p3	0.217	0.21
accruals_p4	-0.401	-0.499	mom12_p4	-0.244	-0.037
accruals_p5	-0.64	-0.504	mom12_p5	-0.435	0.002
accruals_p6	-0.473	-0.33	mom12_p6	-0.37	-0.344
accruals_p7	-0.785	-0.95	mom12_p7	-0.144	-0.049
accruals_p8	-0.68	-0.512	mom12_p8	-0.269	-0.234
accruals_p9	-0.83	-0.239	mom12_p9	-0.45	-0.485
accruals_p10	-0.749	-0.02	mom12_p10	-0.61	-0.494
growth_p1	-0.435	-0.155	momrev_p1	0.244	0.008
growth_p2	-1.183	-0.456	momrev_p2	0.384	0.147
growth_p3	-0.964	-0.596	momrev_p3	-0.173	-0.26
growth_p4	-0.54	-0.612	momrev_p4	-0.45	-0.38
growth_p5	-0.328	-0.74	momrev_p5	-0.565	-0.412
growth_p6	-0.785	-0.76	momrev_p6	-0.243	0.301
growth_p7	-0.816	-0.712	momrev_p7	-0.284	-0.003
growth_p8	-0.548	-0.404	momrev_p8	-0.342	-0.128
growth_p9	-0.343	-0.204	momrev_p9	0.49	1.378
growth_p10	0.227	0.938	momrev_p10	-0.313	0.334
aturnover_p1	-0.568	0.172	lrrev_p1	-0.269	0.895
aturnover_p2	-0.322	-0.276	lrrev_p2	-1.088	-0.791
aturnover_p3	-0.608	-0.319	lrrev_p3	-0.281	-0.201
aturnover_p4	-0.336	-0.313	lrrev_p4	-0.468	-0.529
aturnover_p5	-0.333	-0.244	lrrev_p5	-0.416	-0.399
aturnover_p6	-0.69	-0.721	lrrev_p6	-0.681	-0.364
aturnover_p7	-0.479	-0.19	lrrev_p7	0.153	-0.094
aturnover_p8	-0.588	-1.071	lrrev_p8	-0.673	-0.605
aturnover_p9	-1.681	-2.53	lrrev_p9	-0.068	-0.187
aturnover_p10	-1.621	-0.883	lrrev_p10	-0.736	-0.533
gmargins_p1	0.16	-0.41	valuem_p1	-0.412	0.152
gmargins_p2	-0.227	-0.443	valuem_p2	-0.736	-0.804
gmargins_p3	-0.588	-0.667	valuem_p3	-0.469	-0.453
gmargins_p4	-0.368	-0.509	valuem_p4	-0.14	-0.201
gmargins_p5	-0.614	-0.311	valuem_p5	-0.648	-0.535
gmargins_p6	0.173	0.017	valuem_p6	-0.559	-0.592
gmargins_p7	0.154	0.367	valuem_p7	0.073	0.075
gmargins_p8	-0.779	-0.64	valuem_p8	-0.52	-0.313
gmargins_p9	-0.385	-0.518	valuem_p9	0.875	1.003

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Table C.9 – continued from previous page

Deciles	1992m12	2004m12	Deciles	1992m12	2004m12
gmargins__p10	-0.631	-0.345	valuem__p10	1.647	2.74
divp__p1	-0.469	0.227	nissm__p1	1.797	2.521
divp__p2	-0.697	-0.398	nissm__p2	-0.526	-0.116
divp__p3	-0.441	-0.301	nissm__p3	-0.331	-0.036
divp__p4	-0.307	0.052	nissm__p4	-0.173	-0.142
divp__p5	-0.629	-0.493	nissm__p5	-0.254	-0.209
divp__p6	-0.161	-0.232	nissm__p6	-0.487	-0.455
divp__p7	-0.707	-0.73	nissm__p7	-0.798	-0.547
divp__p8	-0.705	-0.784	nissm__p8	-0.541	-0.416
divp__p9	-1.235	-0.797	nissm__p9	-0.26	-0.322
divp__p10	1.382	1.323	nissm__p10	-0.451	-0.224
divg__p1	-0.723	-0.683	sue__p1	-0.631	-0.298
divg__p2	-0.622	-0.759	sue__p2	-0.583	-0.489
divg__p3	-0.545	-0.604	sue__p3	0.113	0.296
divg__p4	-0.312	-0.243	sue__p4	-0.26	-0.119
divg__p5	-0.39	-0.249	sue__p5	-0.577	-0.614
divg__p6	-0.004	0.032	sue__p6	-0.471	-0.747
divg__p7	-0.474	-0.466	sue__p7	-0.341	-0.254
divg__p8	-0.374	-0.195	sue__p8	-0.419	-0.416
divg__p9	-0.719	-0.456	sue__p9	-0.4	-0.314
divg__p10	-0.371	-0.121	sue__p10	-0.694	-1.208
dur__p1	-0.646	0.211	roe__p1	1.487	2.48
dur__p2	-0.696	-0.522	roe__p2	1.269	1.934
dur__p3	-0.267	-0.772	roe__p3	-0.101	0.467
dur__p4	-0.064	-0.183	roe__p4	-0.271	-0.242
dur__p5	-0.426	-0.441	roe__p5	-0.946	-0.457
dur__p6	-0.393	-0.532	roe__p6	-0.066	-0.189
dur__p7	-0.627	-0.568	roe__p7	-0.396	-0.514
dur__p8	-0.294	-0.43	roe__p8	-0.466	-0.384
dur__p9	-0.448	-0.443	roe__p9	-0.646	-0.578
dur__p10	0.777	1.027	roe__p10	-0.862	-0.274
ep__p1	1.444	2.514	rome__p1	3.048	3.983
ep__p2	-0.395	0.183	rome__p2	1.11	1.549
ep__p3	-0.475	-0.395	rome__p3	-0.612	-0.086
ep__p4	-0.6	-0.506	rome__p4	-0.382	-0.23
ep__p5	-0.502	-0.531	rome__p5	-0.179	-0.177
ep__p6	-0.397	-0.479	rome__p6	-0.419	-0.369
ep__p7	-0.483	-0.514	rome__p7	-0.464	-0.427

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Table C.9 – continued from previous page

Deciles	1992m12	2004m12	Deciles	1992m12	2004m12
ep__p8	0.018	0.113	rome__p8	-0.572	-0.614
ep__p9	0.661	0.675	rome__p9	-0.263	-0.709
ep__p10	-0.196	-0.367	rome__p10	-0.489	-0.612
cfp__p1	-0.297	0.304	roa__p1	0.822	1.238
cfp__p2	-0.277	-0.23	roa__p2	1.89	2.703
cfp__p3	-0.651	-0.427	roa__p3	-0.691	0.029
cfp__p4	-0.44	-0.285	roa__p4	-0.549	-0.562
cfp__p5	-0.405	-0.116	roa__p5	-0.321	-0.49
cfp__p6	-0.196	0.033	roa__p6	-0.567	-0.581
cfp__p7	-0.433	-0.192	roa__p7	-0.905	-0.702
cfp__p8	-0.872	-0.577	roa__p8	-0.44	-0.677
cfp__p9	-0.821	-0.677	roa__p9	-0.238	-0.385
cfp__p10	0.439	0.571	roa__p10	-0.883	-0.326
noa__p1	-0.409	0.213	strev__p1	-0.5	-0.386
noa__p2	0.564	0.163	strev__p2	-0.328	-0.106
noa__p3	-0.507	-0.369	strev__p3	-0.46	0.038
noa__p4	0.609	0.205	strev__p4	-0.491	-0.187
noa__p5	-0.419	-0.717	strev__p5	-0.479	-0.659
noa__p6	-0.513	-1.156	strev__p6	-0.407	-0.615
noa__p7	-0.435	-0.448	strev__p7	-0.81	-0.901
noa__p8	-0.592	-0.578	strev__p8	-0.471	-1.802
noa__p9	-0.745	-0.422	strev__p9	-0.226	-0.122
noa__p10	-0.838	0.152	strev__p10	0.028	0.682
inv__p1	-0.399	0.088	ivol__p1	0.161	1.699
inv__p2	-0.785	-0.486	ivol__p2	0.615	2.698
inv__p3	-0.196	-0.648	ivol__p3	0.248	0.677
inv__p4	-0.095	0.197	ivol__p4	0.531	0.788
inv__p5	-0.851	-0.785	ivol__p5	0.218	0.276
inv__p6	-0.696	-0.731	ivol__p6	-0.226	-0.181
inv__p7	-0.593	-0.406	ivol__p7	-0.219	-0.016
inv__p8	-0.599	-0.498	ivol__p8	-0.693	-0.586
inv__p9	-0.361	-0.56	ivol__p9	-0.561	-0.492
inv__p10	-0.389	0.052	ivol__p10	-0.391	-0.419
invcap__p1	-0.379	0.156	betaarb__p1	0.113	0.624
invcap__p2	-1.025	-0.266	betaarb__p2	0.103	0.249
invcap__p3	-0.46	-0.581	betaarb__p3	-0.093	-0.101
invcap__p4	-0.364	0.015	betaarb__p4	0.097	0.281
invcap__p5	-0.438	-0.412	betaarb__p5	-0.724	-0.785

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Table C.9 – continued from previous page

Deciles	1992m12	2004m12	Deciles	1992m12	2004m12
invcap__p6	-0.347	-0.194	betaarb__p6	-0.645	-0.56
invcap__p7	-0.552	-0.531	betaarb__p7	-0.386	-0.699
invcap__p8	-0.859	-0.415	betaarb__p8	-0.448	-0.859
invcap__p9	-1.047	-0.711	betaarb__p9	-0.292	-0.565
invcap__p10	-0.569	-0.545	betaarb__p10	-0.579	-1.718
igrowth__p1	-0.489	-0.726	season__p1	-0.444	-0.119
igrowth__p2	-0.718	-0.142	season__p2	-0.655	-0.701
igrowth__p3	-0.544	-0.451	season__p3	-0.585	-0.413
igrowth__p4	-0.533	-0.75	season__p4	-0.482	-0.504
igrowth__p5	-0.666	-0.524	season__p5	-0.24	-0.207
igrowth__p6	-0.605	-1.054	season__p6	-0.397	-0.325
igrowth__p7	-0.602	-0.461	season__p7	0.01	0.037
igrowth__p8	-0.603	-0.798	season__p8	-0.587	-0.4
igrowth__p9	-0.279	-0.312	season__p9	-0.383	-0.098
igrowth__p10	-0.562	-0.126	season__p10	-0.551	0.033
sgrowth__p1	-0.621	-0.026	indrrev__p1	-0.217	0.449
sgrowth__p2	-0.846	-0.508	indrrev__p2	-0.227	0.005
sgrowth__p3	-0.657	-0.4	indrrev__p3	0.025	0.424
sgrowth__p4	-0.517	-0.53	indrrev__p4	-0.308	-0.272
sgrowth__p5	-0.551	-0.774	indrrev__p5	-0.643	-0.267
sgrowth__p6	-0.377	-0.479	indrrev__p6	-0.411	-0.537
sgrowth__p7	-0.597	-0.658	indrrev__p7	-0.806	-0.854
sgrowth__p8	-0.806	-0.691	indrrev__p8	-0.512	-0.731
sgrowth__p9	0.338	0.623	indrrev__p9	-0.052	0.46
sgrowth__p10	-0.241	0.081	indrrev__p10	-0.638	0.016
lev__p1	-0.667	-0.161	indrrevlv__p1	-0.271	-0.322
lev__p2	-0.308	-0.292	indrrevlv__p2	-0.458	-0.417
lev__p3	-0.407	-0.726	indrrevlv__p3	-0.228	-0.595
lev__p4	-0.655	-0.797	indrrevlv__p4	-0.69	-0.769
lev__p5	-0.781	-0.771	indrrevlv__p5	-0.576	-0.783
lev__p6	-0.52	-0.306	indrrevlv__p6	-0.45	-0.446
lev__p7	-0.725	-0.664	indrrevlv__p7	-0.632	-0.492
lev__p8	-0.039	0.248	indrrevlv__p8	-0.627	-0.516
lev__p9	-0.877	-0.091	indrrevlv__p9	-0.515	-0.885
lev__p10	0.253	1.632	indrrevlv__p10	-0.722	-0.574
roaa__p1	0.689	1.085	indmomrev__p1	-0.506	0.133
roaa__p2	1.195	2.099	indmomrev__p2	-0.593	-0.543
roaa__p3	-0.591	0.017	indmomrev__p3	-0.469	-0.147

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Table C.9 – continued from previous page

Deciles	1992m12	2004m12	Deciles	1992m12	2004m12
roaa__p4	-0.5	-0.551	indmomrev__p4	-0.584	-0.262
roaa__p5	-0.812	-0.605	indmomrev__p5	-0.578	-0.304
roaa__p6	-0.459	-0.031	indmomrev__p6	-0.164	0.14
roaa__p7	-0.3	-0.358	indmomrev__p7	-0.183	-0.15
roaa__p8	-0.385	-0.454	indmomrev__p8	-0.465	-0.4
roaa__p9	-0.663	-0.446	indmomrev__p9	-0.508	-0.358
roaa__p10	-1.018	-0.301	indmomrev__p10	-0.544	-0.692
roea__p1	0.784	1.508	ciss__p1	-0.033	0.013
roea__p2	0.231	0.678	ciss__p2	-0.588	-0.061
roea__p3	-0.034	0.152	ciss__p3	-0.116	-0.05
roea__p4	-1.16	-0.583	ciss__p4	-0.494	-0.318
roea__p5	-0.544	-0.458	ciss__p5	-0.413	-0.58
roea__p6	-0.401	-0.354	ciss__p6	-0.869	-0.373
roea__p7	-0.337	-0.266	ciss__p7	-0.479	-0.573
roea__p8	-0.384	0.128	ciss__p8	-0.561	-0.597
roea__p9	-0.681	-0.693	ciss__p9	-0.399	-0.291
roea__p10	-1.156	0.145	ciss__p10	0.636	0.83
sp__p1	-0.407	0.076	price__p1	0.886	3.231
sp__p2	-0.391	-0.226	price__p2	0.837	1.694
sp__p3	-0.467	-0.441	price__p3	-0.405	0.522
sp__p4	-0.347	-0.298	price__p4	0.039	-0.268
sp__p5	-0.453	-0.557	price__p5	-0.43	-0.344
sp__p6	0.682	1.089	price__p6	-0.251	-0.126
sp__p7	0.077	-0.096	price__p7	-0.284	-0.206
sp__p8	-0.551	-1.417	price__p8	-0.58	-0.431
sp__p9	0.427	-1.766	price__p9	-0.401	-0.242
sp__p10	1.067	-0.97	price__p10	-0.425	-0.285
gltnoa__p1	0.299	0.45	shvol__p1	0.04	1.381
gltnoa__p2	-0.28	0.079	shvol__p2	-0.204	0.043
gltnoa__p3	-0.44	-0.092	shvol__p3	0.33	0.598
gltnoa__p4	-0.702	-0.812	shvol__p4	0.137	0.57
gltnoa__p5	-0.321	-1.404	shvol__p5	-0.536	-0.626
gltnoa__p6	-0.419	-0.893	shvol__p6	-0.304	-0.128
gltnoa__p7	-0.032	0.005	shvol__p7	-0.477	-0.407
gltnoa__p8	-0.525	-0.462	shvol__p8	-0.615	-0.47
gltnoa__p9	-0.789	-0.523	shvol__p9	-0.372	-0.303
gltnoa__p10	-0.881	-0.073	shvol__p10	0.002	-0.933

Table C.10: R^2_{oos} of the univariate predictive models using other variables (%)

This table presents the R^2_{oos} of the univariate predictive model using fourteen financial, macroeconomic variables as predictors. We use 1992m12 as split date. We compute the out-of-sample R^2_{oos} using equation 3.7. Predictors are those used by Welch and Goyal (2008) augmented by the Chicago Fed activity index: book-to-market (b.m), Treasury bills (tbl), long-term yield (lty), net equity expansion (ntis), inflation (infl), long-term rate of return (ltr), corporate bond return (corpr), stock variance (svar), Dividend price ratio (Dpr), Dividend yield (Dy), Earning price ratio (Epr), Dividend Payout Ratio (Der), Default yield spread (Dfy), Chicago Fed National Activity Index (gro_p). See section 3.2.1 in the main text for more details.

	b.m	tbl	lty	ntis	infl	ltr	corpr	svar	Dpr	Dy	Epr	Der	Dfy	gro_p
size_p1	0.17	-0.84	-0.69	-1.93	-1.20	0.10	0.66	1.22	0.14	0.48	0.18	-1.49	-1.14	0.91
size_p2	0.06	-0.93	-0.72	-1.42	-0.97	0.67	1.94	1.15	-0.58	0.17	-0.56	-1.70	-1.24	-0.45
size_p3	0.00	-0.81	-0.74	-0.91	-0.90	0.25	1.23	0.40	-0.76	0.00	-0.66	-1.31	-1.16	-0.77
size_p4	-0.09	-0.83	-0.76	-0.93	-0.80	0.26	1.63	0.41	-0.91	-0.09	-0.78	-1.36	-1.30	-0.93
size_p5	0.25	-0.94	-0.80	-0.73	-1.13	0.21	0.85	0.17	-0.28	0.46	-0.31	-1.22	-1.13	-1.12
size_p6	0.07	-0.76	-0.71	-0.64	-0.95	0.12	0.31	0.21	-0.75	0.01	-0.70	-1.46	-1.25	-0.96
size_p7	-0.10	-0.74	-0.63	-0.54	-0.89	0.16	0.43	0.21	-1.12	-0.11	-0.87	-1.41	-1.40	-1.07
size_p8	-0.22	-0.80	-0.75	-0.55	-0.88	0.24	0.73	0.32	-1.18	-0.33	-0.91	-1.40	-1.24	-0.70
size_p9	-0.76	-0.72	-0.67	-0.38	-0.72	-0.11	-0.11	0.13	-1.99	-1.19	-1.26	-1.52	-1.51	-0.85
size_p10	-0.93	-0.82	-0.91	-0.01	-0.71	-0.45	0.48	1.02	-2.02	-1.46	-1.39	-1.00	-1.23	-0.76
value_p1	-0.22	-1.66	-1.28	-1.81	-1.12	0.08	0.53	0.66	-0.45	-0.23	-0.35	-1.07	-0.89	-0.51
value_p2	0.35	-1.15	-0.86	-1.41	-1.07	0.50	2.00	0.34	0.05	0.63	-0.06	-1.04	-1.31	-0.92
value_p3	-0.20	-1.01	-0.86	-1.43	-1.20	-0.45	-0.33	0.32	-0.98	-0.03	-0.50	-1.04	-1.30	-0.11
value_p4	0.42	-0.97	-0.93	-1.53	-0.80	1.03	2.33	1.36	-0.19	0.66	0.12	-2.06	-1.40	0.42
value_p5	-0.10	-1.16	-0.85	-1.50	-0.66	0.39	1.06	0.21	-0.82	-0.20	-0.46	-1.49	-0.79	0.89
value_p6	-0.25	-0.40	-0.59	-1.44	-0.54	0.30	0.98	0.53	-1.28	-0.31	-0.46	-1.77	-1.51	0.53
value_p7	0.06	-0.61	-0.60	-1.15	-1.58	0.91	2.49	1.25	-0.31	0.15	-0.44	-1.64	-1.49	-0.28
value_p8	0.07	-0.27	-0.33	-1.29	-0.76	0.19	1.08	0.32	-0.83	-0.06	-0.44	-1.65	-1.16	0.10
value_p9	0.59	-0.19	-0.25	-1.04	-1.01	1.28	2.92	0.44	0.40	1.06	-0.31	-1.72	-0.94	0.29
value_p10	0.31	-0.78	-0.25	-0.29	-1.18	0.64	1.37	-0.15	0.02	0.49	-0.69	-1.74	-1.30	0.52
prof_p1	-0.11	-0.33	-0.50	-1.13	-0.83	-0.41	-0.14	0.48	-0.68	-0.02	0.06	-1.17	-1.62	-1.00
prof_p2	0.77	-0.14	-0.29	-1.11	-0.37	0.35	0.79	1.23	0.36	1.00	0.11	-2.49	-1.10	0.37
prof_p3	0.23	-1.19	-1.05	-1.33	-0.67	0.51	2.22	0.85	0.00	0.38	-0.07	-1.87	-0.81	1.63
prof_p4	0.15	-1.18	-1.27	-1.06	-0.79	0.54	2.40	0.71	0.17	0.54	-0.48	-1.55	-0.63	0.92
prof_p5	0.41	-1.01	-0.93	-1.22	-0.72	-0.06	0.54	0.53	-0.07	0.57	0.15	-1.46	-1.06	1.49
prof_p6	0.12	-1.03	-0.95	-1.04	-1.28	-0.09	0.08	0.45	-0.35	0.23	-0.07	-1.24	-0.90	0.63
prof_p7	-0.42	-0.68	-0.69	-1.29	-0.65	0.53	0.55	-0.28	-1.17	-0.32	-0.54	-0.99	-1.37	-0.06
prof_p8	0.07	-0.82	-0.61	-1.17	-1.01	0.47	1.56	0.07	-0.32	0.30	-0.33	-0.82	-1.23	-0.79
prof_p9	0.61	-1.20	-0.66	-1.57	-1.43	0.53	0.61	0.36	0.73	1.12	0.56	-1.00	-1.28	-1.03
prof_p10	-0.05	-0.64	-0.40	-2.07	-1.88	0.30	0.50	1.04	-0.58	-0.06	-0.56	-1.29	-2.20	-1.52
valprof_p1	0.01	-1.30	-1.65	-1.23	-0.62	-0.07	0.40	1.14	-0.30	0.14	-0.34	-1.95	-0.85	0.15
valprof_p2	-0.30	-0.81	-0.80	-1.10	-0.47	-0.01	0.95	0.28	-0.77	-0.22	-0.52	-1.22	-0.59	0.59
valprof_p3	0.36	-0.96	-0.76	-1.39	-0.90	0.89	1.70	0.38	0.41	0.83	-0.19	-0.90	-0.81	0.56

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Table C.10 – continued from previous page

	b.m	tbl	lty	ntis	infl	ltr	corpr	svar	Dpr	Dy	Epr	Der	Dfy	gro_p
valprof_p4	0.35	-0.58	-0.60	-1.46	-0.88	-0.01	0.36	0.03	-0.35	0.31	0.47	-1.11	-1.10	-0.26
valprof_p5	0.25	-0.30	-0.55	-1.40	-0.68	0.50	1.53	0.99	-0.24	0.50	-0.33	-1.41	-1.01	-0.06
valprof_p6	-0.23	-1.31	-0.67	-1.49	-1.83	0.61	1.21	0.36	-0.82	-0.40	-0.22	-1.29	-1.10	0.19
valprof_p7	-0.38	-0.74	-0.60	-1.19	-1.14	0.49	1.28	0.42	-1.23	-0.46	-0.81	-1.50	-1.83	0.26
valprof_p8	-0.52	-0.65	-0.55	-1.57	-1.40	0.26	0.46	-0.26	-1.66	-0.62	-0.95	-1.27	-1.61	-0.19
valprof_p9	0.07	-0.61	-0.40	-0.78	-1.62	1.02	1.84	0.29	-0.76	0.09	-0.96	-1.65	-1.76	-0.30
valprof_p10	0.32	-0.51	-0.08	-0.72	-1.68	0.51	0.93	0.45	-0.52	0.37	-0.77	-1.50	-1.83	-0.98
nissa_p1	0.10	-0.74	-0.79	-1.07	-0.71	0.10	1.27	1.29	0.07	0.62	-0.50	-1.40	-0.97	-1.34
nissa_p2	-0.06	-0.54	-0.61	-0.76	-0.87	-0.25	0.48	1.11	-0.49	0.11	-0.62	-1.05	-0.85	-0.31
nissa_p3	-0.39	-0.73	-0.67	-0.73	-0.85	0.08	0.75	0.57	-1.32	-0.76	-0.55	-1.12	-0.94	0.30
nissa_p4	-0.06	-0.88	-0.74	-1.11	-0.91	-0.03	1.04	0.60	-0.63	0.09	-0.44	-1.16	-1.38	-0.57
nissa_p5	0.12	-1.00	-0.93	-1.16	-0.64	0.11	0.56	2.19	-0.35	0.34	-0.56	-2.22	-1.36	-0.27
nissa_p6	0.58	-0.83	-0.53	-1.20	-0.81	0.33	1.19	1.06	0.16	0.78	0.09	-1.45	-1.28	0.01
nissa_p7	0.64	-1.15	-0.64	-1.76	-1.31	0.35	0.64	1.41	0.43	1.00	0.10	-1.79	-1.77	0.40
nissa_p8	-0.07	-0.87	-0.84	-1.42	-0.87	0.37	0.68	1.14	-1.32	-0.16	-0.23	-1.76	-1.78	0.66
nissa_p9	-0.09	-0.63	-0.54	-2.15	-1.33	0.91	2.51	-0.19	-0.98	-0.03	-0.14	-1.27	-1.50	0.86
nissa_p10	-0.14	-0.67	-0.57	-1.10	-1.41	0.68	1.68	0.76	-0.88	-0.19	-0.73	-1.64	-1.39	-0.12
accruals_p1	0.04	-1.28	-1.07	-0.59	-0.73	0.29	0.64	0.13	-0.39	0.23	-0.36	-1.06	-0.71	-0.58
accruals_p2	0.18	-0.97	-0.86	-1.09	-0.99	0.20	1.34	0.92	-0.20	0.24	-0.12	-1.34	-1.03	-0.47
accruals_p3	-0.08	-1.17	-0.73	-0.77	-1.14	0.33	1.13	-0.20	-0.44	0.11	-0.14	-1.00	-1.23	0.08
accruals_p4	0.32	-0.69	-0.39	-2.03	-1.09	0.27	1.79	0.11	-0.40	0.45	0.22	-1.09	-1.53	0.24
accruals_p5	0.38	-1.19	-0.82	-1.69	-1.35	0.79	1.01	0.37	0.26	0.80	-0.03	-1.53	-1.21	0.77
accruals_p6	0.21	-0.90	-0.77	-2.03	-1.17	0.19	0.74	0.79	0.01	0.35	-0.11	-1.33	-0.87	0.53
accruals_p7	0.31	-0.61	-0.59	-2.31	-1.24	0.65	1.01	0.64	0.21	0.63	0.10	-1.92	-1.30	0.73
accruals_p8	0.18	-0.30	-0.45	-2.09	-1.03	0.25	0.63	1.19	-0.51	0.35	0.07	-1.43	-1.78	0.37
accruals_p9	-0.19	-0.81	-1.02	-0.68	-0.68	-0.11	0.18	0.29	-0.75	-0.31	-0.49	-1.11	-0.59	0.50
accruals_p10	-0.16	-0.82	-0.91	-0.82	-0.67	0.27	1.38	0.23	-0.67	-0.06	-0.65	-0.87	-0.71	-0.40
growth_p1	0.01	-1.22	-1.25	-0.76	-0.77	0.77	1.72	0.08	-0.33	0.24	-0.34	-1.05	-0.60	-0.65
growth_p2	-0.32	-0.73	-0.91	-0.85	-0.57	0.26	0.86	0.88	-1.03	-0.44	-0.69	-1.14	-0.79	-0.11
growth_p3	-0.32	-1.35	-0.88	-1.21	-1.20	0.00	0.47	0.47	-1.09	-0.50	-0.60	-1.13	-1.05	0.74
growth_p4	-0.34	-0.51	-0.50	-2.24	-0.78	-0.07	0.13	0.06	-1.78	-0.55	-0.42	-1.40	-1.89	0.34
growth_p5	0.53	-0.91	-0.54	-1.97	-1.62	0.54	1.83	1.10	0.08	0.70	0.56	-1.27	-1.24	0.80
growth_p6	0.07	-0.52	-0.51	-1.67	-0.76	0.31	0.53	0.60	-0.28	0.31	-0.66	-1.62	-1.52	0.07
growth_p7	0.50	-0.54	-0.41	-1.30	-1.17	0.76	1.78	0.52	0.44	0.75	0.66	-1.43	-1.48	0.62
growth_p8	0.53	-0.84	-0.81	-2.00	-1.01	-0.07	0.46	0.55	0.14	0.67	0.35	-1.44	-1.11	0.58
growth_p9	0.54	-1.02	-1.13	-1.22	-1.34	0.36	0.76	0.51	0.51	1.03	-0.30	-1.62	-1.23	-0.73
growth_p10	-0.55	-0.92	-1.18	-0.52	-1.02	-0.12	0.99	1.02	-1.41	-0.42	-1.65	-1.06	-1.05	-0.47
aturnover_p1	0.17	-0.22	-0.41	-1.02	-0.77	-0.10	0.23	0.43	0.01	0.30	-0.01	-1.91	-0.91	-0.17

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Table C.10 – continued from previous page

	b.m	tbl	lty	ntis	infl	ltr	corpr	svar	Dpr	Dy	Epr	Der	Dfy	gro_p
aturnover_p2	0.64	-0.65	-0.87	-1.38	-0.35	0.26	0.94	0.33	0.35	0.87	0.39	-1.55	-0.68	0.55
aturnover_p3	-0.12	-1.03	-0.85	-1.49	-1.07	0.00	0.21	0.29	-0.27	0.21	-0.45	-1.02	-1.04	-0.15
aturnover_p4	-0.44	-0.83	-0.88	-0.94	-0.46	0.29	0.92	0.66	-1.16	-0.15	-0.50	-1.11	-1.08	1.08
aturnover_p5	0.13	-1.12	-0.92	-1.30	-1.29	0.26	1.20	1.69	-0.12	0.52	-0.52	-1.22	-1.52	0.17
aturnover_p6	0.16	-0.95	-1.01	-1.36	-0.72	0.57	1.85	0.13	0.05	0.45	-0.50	-1.58	-0.93	0.32
aturnover_p7	0.13	-0.89	-0.64	-1.36	-1.08	0.58	1.61	1.29	-0.34	0.27	-0.39	-1.36	-1.05	0.33
aturnover_p8	0.42	-0.95	-0.74	-1.09	-1.46	0.24	0.98	-0.43	-0.16	0.51	0.33	-1.22	-1.16	0.78
aturnover_p9	-0.36	-0.97	-0.70	-1.37	-1.56	0.66	0.83	0.03	-1.46	-0.88	-0.86	-1.35	-1.55	-1.05
aturnover_p10	0.71	-0.55	-0.27	-1.56	-1.96	0.50	0.83	0.16	-0.09	0.57	0.29	-1.04	-1.85	-1.99
gmargins_p1	-0.07	-0.95	-0.96	-0.97	-0.50	0.49	1.99	0.35	-0.92	-0.07	-0.40	-1.46	-1.05	0.40
gmargins_p2	-0.02	-1.13	-0.96	-1.04	-1.32	0.74	1.94	0.94	-0.47	0.03	-0.68	-1.78	-1.16	0.36
gmargins_p3	0.09	-0.69	-0.64	-1.04	-1.18	0.43	1.27	0.50	-0.62	0.16	-0.20	-1.52	-1.35	0.60
gmargins_p4	0.46	-1.18	-0.85	-1.01	-1.04	0.21	1.18	-0.03	-0.14	0.61	0.70	-0.91	-0.98	1.28
gmargins_p5	0.16	-1.11	-0.89	-1.44	-1.35	-0.07	0.49	0.92	-0.16	0.31	-0.22	-1.68	-1.13	0.81
gmargins_p6	0.61	-0.83	-0.68	-1.31	-1.09	0.23	1.28	1.11	0.45	1.06	-0.44	-1.28	-0.84	-0.05
gmargins_p7	0.26	-0.59	-0.64	-1.35	-0.59	0.85	2.22	0.08	-0.25	0.23	-0.53	-1.46	-1.07	-0.72
gmargins_p8	0.21	-0.58	-0.66	-1.50	-1.07	0.52	1.30	0.06	0.11	0.48	-0.27	-1.21	-0.79	-0.43
gmargins_p9	0.72	-0.92	-0.79	-1.59	-0.88	0.16	0.46	0.78	0.78	1.17	0.94	-1.29	-1.28	0.11
gmargins_p10	-0.26	-0.92	-0.74	-1.57	-0.89	0.16	0.49	0.32	-0.66	-0.15	-0.42	-1.05	-1.29	-0.76
divp_p1	0.31	-1.13	-1.13	-1.00	-0.61	0.07	1.53	1.43	-0.20	0.44	-0.32	-1.21	-0.94	-0.38
divp_p2	-0.06	-1.27	-1.03	-1.16	-0.67	0.28	1.72	0.37	-0.61	0.02	-0.55	-1.43	-0.93	-0.31
divp_p3	0.19	-0.93	-0.68	-1.86	-1.11	-0.02	0.72	1.22	-0.16	0.49	-0.03	-1.52	-1.43	-0.41
divp_p4	0.16	-0.82	-0.80	-1.89	-1.07	0.37	1.42	1.79	-0.58	0.23	0.02	-1.54	-1.25	0.21
divp_p5	0.13	-1.19	-0.82	-1.66	-1.55	0.26	1.56	0.09	-0.46	0.07	0.57	-1.12	-1.35	-0.19
divp_p6	-0.13	-0.93	-0.71	-1.71	-1.28	-0.06	1.42	0.68	-0.68	-0.13	-0.09	-1.26	-1.20	0.66
divp_p7	0.18	-0.10	-0.04	-0.99	-0.46	-0.25	-0.04	1.44	-0.89	0.47	0.31	-2.03	-2.24	0.47
divp_p8	0.04	-0.82	-0.39	-1.49	-1.71	0.30	-0.48	1.57	-0.31	0.22	-1.07	-3.24	-2.07	-0.72
divp_p9	-0.02	-0.35	-0.41	-1.54	-1.40	0.35	0.89	0.59	-0.52	0.02	-0.90	-2.14	-1.65	0.14
divp_p10	-0.05	-0.39	-0.40	-0.96	-0.34	-0.25	-0.73	3.23	-0.35	-0.06	-1.18	-4.19	-2.05	0.14
divg_p1	0.98	-0.58	-0.39	-0.96	-0.71	0.35	1.55	1.60	1.56	1.95	-0.28	-0.61	-0.80	-0.24
divg_p2	-0.12	-0.71	-0.62	-0.96	-1.03	0.77	1.59	1.57	-0.77	0.15	-0.57	-1.89	-2.05	0.15
divg_p3	-0.01	-0.53	-0.47	-1.87	-0.57	0.59	1.45	1.66	-0.77	0.43	-0.51	-2.23	-1.67	0.40
divg_p4	0.38	-0.73	-0.76	-1.68	-0.61	0.36	1.38	1.44	-0.26	0.47	0.38	-1.46	-1.10	0.78
divg_p5	0.42	-0.15	-0.22	-1.73	-1.05	-0.64	0.52	0.75	0.16	0.71	0.16	-1.54	-1.08	0.50
divg_p6	0.27	-0.62	-0.47	-1.58	-1.25	-0.32	-0.33	2.28	-0.17	0.53	0.20	-2.23	-2.19	0.09
divg_p7	0.10	-0.85	-0.51	-2.00	-1.86	0.04	0.54	0.85	-0.40	0.12	0.12	-1.64	-1.40	0.26
divg_p8	0.11	-0.72	-0.46	-1.70	-1.14	0.22	0.19	1.51	-0.50	0.26	-0.41	-2.17	-2.17	-0.09
divg_p9	0.12	-1.49	-1.13	-1.47	-1.43	-0.02	0.44	0.99	0.00	0.22	0.35	-1.31	-0.99	0.43

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Table C.10 – continued from previous page

	b.m	tbl	lty	ntis	infl	ltr	corpr	svar	Dpr	Dy	Epr	Der	Dfy	gro_p
divg_p10	0.05	-1.23	-1.13	-1.33	-0.95	1.61	3.05	0.60	-0.68	0.04	-0.34	-1.79	-1.23	-0.45
dur_p1	-0.22	-1.71	-1.48	-1.79	-1.11	0.19	0.81	0.47	-0.37	-0.24	-0.41	-1.04	-0.78	-0.61
dur_p2	0.02	-1.21	-0.89	-1.36	-0.85	0.38	1.65	0.62	-0.47	0.19	-0.12	-1.17	-1.29	-1.09
dur_p3	-0.26	-0.90	-0.72	-1.29	-1.12	-0.12	0.60	0.31	-1.10	-0.15	-0.51	-1.06	-1.44	-0.12
dur_p4	0.03	-1.17	-1.00	-1.82	-1.36	0.50	0.79	0.78	-0.86	0.06	-0.06	-1.68	-1.53	0.54
dur_p5	0.18	-0.97	-0.73	-1.27	-0.90	0.34	1.63	0.53	-0.57	0.27	-0.14	-1.32	-1.10	0.70
dur_p6	-0.15	-1.19	-1.00	-1.39	-0.73	0.60	1.17	0.39	-0.64	-0.29	-0.77	-1.69	-0.95	0.09
dur_p7	-0.30	-0.51	-0.49	-1.24	-0.98	0.39	0.71	0.78	-1.26	-0.39	-0.54	-1.52	-1.70	0.84
dur_p8	-0.17	-0.58	-0.88	-1.27	-1.33	0.58	1.68	1.11	-0.69	-0.11	-0.52	-1.60	-1.38	-0.24
dur_p9	-0.14	-0.67	-0.51	-0.61	-1.48	0.43	2.10	0.83	-0.70	0.14	-0.98	-1.57	-1.30	0.65
dur_p10	0.18	-0.56	-0.47	-0.09	-0.54	0.78	2.06	-0.55	-0.06	0.29	-0.67	-1.33	-0.73	0.25
ep_p1	-0.31	-1.04	-0.99	-0.34	-0.53	-0.20	0.62	-0.08	-0.76	-0.29	-0.83	-0.66	-0.83	-0.04
ep_p2	-0.22	-0.81	-0.95	-1.52	-0.63	-0.09	0.21	0.37	-0.60	-0.27	-0.70	-0.93	-0.72	-0.65
ep_p3	-0.16	-1.22	-1.14	-1.39	-1.07	0.06	1.17	1.38	-0.60	-0.04	-0.40	-1.20	-1.10	-0.63
ep_p4	0.59	-0.57	-0.65	-2.14	-0.84	0.18	1.45	0.86	0.11	0.71	0.54	-1.23	-1.36	-0.69
ep_p5	-0.19	-1.07	-0.79	-1.21	-0.95	0.35	1.31	0.26	-0.93	-0.24	-0.10	-1.44	-1.17	0.52
ep_p6	0.38	0.25	-0.20	-1.70	-1.03	1.16	2.37	1.59	-0.70	0.33	0.34	-1.89	-2.04	-0.99
ep_p7	-0.01	-0.64	-0.74	-1.63	-0.93	0.81	1.82	1.18	-0.57	0.08	-0.41	-1.54	-1.00	-0.20
ep_p8	0.07	-0.33	-0.20	-1.22	-1.40	0.24	0.78	1.69	-0.70	0.04	-0.30	-2.05	-1.59	0.52
ep_p9	0.21	-0.50	-0.49	-0.54	-1.37	0.85	2.48	1.15	-0.44	0.20	-0.37	-1.96	-1.43	0.08
ep_p10	-0.46	-1.01	-0.56	-0.58	-1.50	0.96	1.58	1.14	-1.29	-0.54	-1.00	-1.93	-1.20	-0.33
cfp_p1	-0.23	-1.51	-1.36	-1.40	-1.05	0.06	0.63	1.29	-0.51	-0.27	-0.39	-1.16	-1.05	-0.64
cfp_p2	-0.12	-1.36	-1.10	-2.35	-1.03	0.08	0.95	0.81	-0.80	-0.09	-0.36	-1.29	-1.35	-1.15
cfp_p3	0.28	-0.88	-0.80	-1.62	-1.16	0.87	2.33	0.57	-0.35	0.43	0.18	-1.40	-1.26	-0.73
cfp_p4	0.31	-0.57	-0.48	-2.12	-1.02	0.48	1.71	1.19	-0.10	0.85	-0.29	-1.71	-2.05	-0.97
cfp_p5	-0.10	-0.55	-0.58	-1.12	-0.70	0.45	1.41	1.73	-1.37	-0.18	-0.05	-1.64	-1.64	0.48
cfp_p6	-0.18	-0.51	-0.52	-1.10	-0.95	0.11	1.26	1.71	-1.17	-0.27	-0.69	-1.85	-1.77	0.01
cfp_p7	0.01	-1.00	-0.66	-1.84	-1.01	0.74	2.17	0.91	-0.62	0.00	-0.70	-2.29	-1.35	0.46
cfp_p8	-0.02	-0.13	-0.38	-1.02	-0.43	0.29	0.98	1.17	-0.86	-0.09	-0.37	-1.78	-1.01	0.23
cfp_p9	-0.01	-0.31	-0.37	-1.27	-1.13	1.01	1.83	-0.05	-0.73	0.07	-0.61	-1.69	-1.14	0.32
cfp_p10	0.08	-0.94	-0.65	-0.55	-0.84	0.95	2.22	0.76	-0.13	0.44	-0.83	-1.70	-0.88	0.30
noa_p1	0.51	-0.77	-0.94	-0.92	-0.74	0.61	1.60	0.32	0.61	1.12	-0.11	-1.41	-0.51	-1.15
noa_p2	-0.11	-0.38	-0.41	-0.68	-0.91	0.18	0.36	1.07	-0.95	-0.36	-0.42	-1.78	-1.24	-0.20
noa_p3	-0.08	-0.70	-0.68	-1.26	-0.93	-0.13	0.47	0.91	-0.58	-0.16	-0.65	-1.62	-1.07	-0.05
noa_p4	0.94	-0.76	-0.96	-1.18	-0.84	1.19	1.67	0.30	1.35	1.46	0.86	-1.93	-0.97	0.17
noa_p5	0.29	-0.91	-0.84	-1.40	-0.76	0.03	0.38	0.10	-0.50	0.25	-0.01	-1.36	-1.20	-0.74
noa_p6	0.88	-0.36	0.11	-0.86	-0.55	0.36	1.48	0.63	0.70	1.27	0.53	-1.28	-1.53	0.98
noa_p7	-0.14	-1.09	-0.97	-1.67	-1.04	0.02	0.90	0.85	-1.13	-0.20	-0.08	-1.34	-1.46	0.85

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Table C.10 – continued from previous page

	b.m	tbl	lty	ntis	infl	ltr	corpr	svar	Dpr	Dy	Epr	Der	Dfy	gro_p
noa_p8	0.32	-1.07	-0.59	-1.10	-1.84	0.10	0.46	1.07	-0.08	0.61	-0.28	-1.40	-1.48	0.86
noa_p9	0.03	-1.11	-1.00	-1.37	-0.87	-0.07	0.36	-0.51	-0.08	0.21	-0.03	-0.99	-0.69	0.45
noa_p10	-0.40	-0.71	-0.62	-0.96	-1.04	0.12	0.74	0.59	-1.04	-0.52	-0.82	-0.80	-1.14	-0.33
inv_p1	0.34	-1.23	-1.43	-1.18	-0.80	0.63	2.09	0.87	0.09	0.60	-0.46	-1.77	-0.80	-0.66
inv_p2	0.41	-0.66	-0.76	-1.06	-0.65	0.19	0.68	-0.11	0.22	0.64	0.05	-1.27	-0.68	-0.12
inv_p3	-0.22	-1.06	-0.79	-1.04	-1.03	0.09	0.17	-0.04	-0.87	-0.30	0.03	-0.85	-1.13	0.64
inv_p4	-0.13	-0.90	-0.55	-1.37	-1.44	0.39	0.80	0.89	-0.67	-0.09	-0.45	-1.41	-1.24	0.92
inv_p5	-0.06	-0.63	-0.65	-1.21	-0.74	0.43	1.55	0.32	-0.58	0.05	-0.47	-1.22	-1.14	0.62
inv_p6	-0.03	-0.55	-0.68	-1.97	-0.85	0.19	1.21	1.14	-0.38	0.06	-0.36	-1.33	-0.98	0.67
inv_p7	0.67	-0.59	-0.52	-1.31	-0.80	-0.22	0.08	0.30	0.50	0.99	0.50	-1.28	-1.23	-0.01
inv_p8	0.23	-1.01	-0.77	-1.91	-0.96	0.92	2.58	0.70	0.03	0.57	-0.40	-1.15	-1.02	-0.32
inv_p9	0.21	-0.36	-0.44	-1.03	-1.33	0.46	0.23	0.43	-0.58	0.33	0.13	-2.20	-2.75	-0.44
inv_p10	0.28	-0.99	-0.82	-0.79	-1.04	0.05	0.61	1.33	-0.17	0.55	-0.74	-1.17	-1.01	0.04
invcap_p1	-0.42	-1.04	-0.93	-0.55	-0.99	0.22	0.38	-0.03	-1.05	-0.67	-0.78	-0.79	-0.80	-0.71
invcap_p2	-0.38	-0.84	-0.76	-0.77	-0.90	0.04	0.61	0.52	-1.19	-0.51	-0.94	-1.14	-1.13	-0.33
invcap_p3	0.40	-0.87	-0.84	-1.65	-0.93	0.18	1.27	0.38	0.35	0.81	-0.13	-1.12	-0.77	0.23
invcap_p4	0.25	-0.63	-0.68	-0.91	-0.72	0.55	1.32	2.44	-0.44	0.40	-0.10	-2.20	-1.56	0.78
invcap_p5	0.76	-0.58	-0.36	-1.60	-1.10	0.64	1.57	0.41	0.73	1.52	0.51	-1.27	-1.31	0.20
invcap_p6	0.34	-1.32	-1.07	-1.87	-1.07	0.39	0.87	0.65	0.07	0.50	0.48	-1.23	-0.98	1.03
invcap_p7	0.85	-0.42	-0.40	-2.66	-1.01	0.69	1.07	0.80	0.39	0.88	1.03	-1.62	-1.79	-0.13
invcap_p8	0.25	-0.28	-0.39	-1.63	-1.00	-0.20	0.32	-0.61	-0.14	0.44	0.71	-1.29	-1.34	0.65
invcap_p9	0.07	-0.25	-0.35	-1.50	-0.53	0.46	2.15	0.06	-0.87	-0.03	0.05	-1.43	-1.29	0.07
invcap_p10	0.21	-0.67	-0.59	-1.32	-1.10	0.73	2.44	1.34	-0.46	0.20	-0.47	-1.52	-0.86	-0.02
igrowth_p1	0.01	-1.01	-1.02	-0.76	-0.67	0.19	0.51	-0.04	-0.48	-0.07	-0.11	-1.03	-0.73	-0.37
igrowth_p2	-0.37	-0.83	-0.89	-0.92	-0.80	0.61	1.54	0.26	-1.14	-0.43	-0.90	-1.37	-0.87	-0.30
igrowth_p3	-0.08	-1.03	-0.86	-1.73	-1.06	0.50	0.82	0.79	-0.40	0.20	-0.49	-1.45	-0.92	0.77
igrowth_p4	0.13	-0.98	-0.78	-1.87	-0.88	0.02	0.72	0.76	-0.48	0.12	0.02	-1.32	-0.98	0.18
igrowth_p5	0.16	-0.95	-0.70	-1.62	-1.13	0.15	0.39	1.03	-0.19	0.31	-0.42	-1.37	-1.30	0.96
igrowth_p6	0.31	-0.43	-0.48	-1.36	-1.20	0.16	1.25	1.10	0.08	0.54	0.26	-1.39	-1.63	0.00
igrowth_p7	0.16	-0.57	-0.55	-1.53	-0.93	0.24	1.20	-0.32	-0.18	0.43	0.54	-1.14	-1.53	0.58
igrowth_p8	0.53	-0.57	-0.52	-1.44	-1.12	0.60	1.54	0.59	0.08	0.79	0.00	-1.52	-1.37	-0.43
igrowth_p9	-0.05	-0.93	-0.90	-0.65	-0.81	0.16	0.81	0.34	-0.78	-0.16	-0.52	-1.09	-0.94	-0.06
igrowth_p10	-0.19	-0.99	-1.09	-0.47	-0.73	-0.18	0.18	0.17	-1.11	-0.27	-0.78	-0.94	-0.75	-0.38
sgrowth_p1	-0.25	-0.97	-1.12	-0.77	-0.68	0.56	1.38	0.30	-0.88	-0.31	-0.54	-1.04	-0.70	-0.55
sgrowth_p2	-0.15	-0.99	-0.96	-0.88	-0.91	0.23	0.41	0.04	-0.64	-0.21	-0.55	-0.99	-0.60	0.58
sgrowth_p3	-0.21	-0.56	-0.58	-1.04	-0.68	0.20	0.98	0.64	-1.24	-0.24	-0.51	-1.24	-1.09	0.03
sgrowth_p4	0.21	-0.25	-0.41	-1.30	-0.75	0.72	0.87	0.05	-0.26	0.48	0.14	-1.45	-1.64	-0.17
sgrowth_p5	0.52	-0.79	-0.26	-1.41	-1.41	0.05	1.20	0.81	0.60	1.09	0.31	-0.95	-1.45	-0.34

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Table C.10 – continued from previous page

	b.m	tbl	lty	ntis	infl	ltr	corpr	svar	Dpr	Dy	Epr	Der	Dfy	gro_p
sgrowth_p6	-0.08	-0.67	-0.54	-1.21	-1.21	0.80	2.01	0.06	-0.96	-0.03	-0.21	-1.41	-1.69	0.44
sgrowth_p7	0.43	-1.21	-0.91	-2.39	-1.13	0.44	0.80	1.18	0.28	0.46	0.64	-1.80	-1.51	0.65
sgrowth_p8	0.27	-0.51	-0.67	-2.02	-0.75	-0.31	0.03	1.14	-0.42	0.34	-0.16	-2.06	-1.77	0.59
sgrowth_p9	-0.14	-0.87	-1.08	-1.80	-0.83	0.25	1.74	0.97	-0.52	0.13	-1.00	-1.48	-0.90	0.09
sgrowth_p10	0.24	-0.93	-1.38	-0.86	-0.82	-0.05	0.62	1.08	0.08	0.59	-0.09	-1.37	-1.07	-0.06
lev_p1	-0.12	-1.22	-1.06	-1.56	-1.14	0.18	0.51	0.44	-0.34	-0.08	-0.32	-0.95	-1.03	-0.89
lev_p2	0.05	-1.42	-0.90	-1.33	-0.98	-0.12	1.14	0.36	-0.78	0.32	0.22	-1.22	-1.59	-0.47
lev_p3	0.58	-0.92	-0.85	-1.46	-0.84	0.81	2.17	0.41	0.54	1.05	0.32	-1.19	-0.98	0.07
lev_p4	-0.20	-1.03	-0.90	-1.79	-0.64	0.90	1.72	0.84	-1.13	-0.37	-0.69	-2.09	-0.99	1.08
lev_p5	0.20	-1.08	-0.80	-1.40	-1.61	0.45	1.44	0.53	-0.13	0.19	0.03	-1.54	-1.08	0.52
lev_p6	0.35	-0.28	-0.36	-1.75	-0.76	0.23	1.13	1.47	-0.74	0.47	-0.08	-1.98	-1.41	0.70
lev_p7	-0.12	-0.07	-0.30	-1.11	-0.78	0.21	2.00	1.13	-0.97	-0.04	-0.70	-1.75	-1.51	-0.20
lev_p8	0.07	-0.42	-0.39	-0.87	-1.22	0.67	1.21	1.07	-0.46	0.23	-0.64	-2.63	-1.73	-0.15
lev_p9	0.17	-0.48	-0.37	-0.70	-1.33	0.58	0.98	1.20	-0.32	0.32	-0.44	-1.82	-1.84	-0.36
lev_p10	-0.17	-0.50	-0.41	-0.39	-1.26	-0.51	-0.48	2.56	-0.72	-0.12	-1.10	-2.93	-1.88	-1.03
roaa_p1	-0.34	-0.54	-0.74	-0.48	-0.46	-0.23	0.65	-0.09	-0.75	-0.24	-0.85	-0.64	-0.80	-0.65
roaa_p2	0.10	-0.57	-0.51	-0.44	-0.75	-0.16	0.04	2.39	-0.52	0.26	-0.94	-3.05	-1.77	-0.07
roaa_p3	-0.32	-0.42	-0.54	-1.05	-1.22	-0.24	-0.38	1.67	-0.99	-0.16	-1.06	-2.28	-2.27	-1.07
roaa_p4	-0.08	-0.50	-0.61	-1.19	-1.30	0.06	0.19	1.02	-0.67	-0.12	-0.48	-2.19	-1.66	-0.86
roaa_p5	0.67	-0.60	-0.56	-1.11	-0.97	0.65	1.60	0.43	0.55	0.92	0.61	-1.33	-1.09	0.44
roaa_p6	0.82	-0.51	-0.39	-1.25	-0.32	-0.07	0.50	1.67	0.09	1.03	0.41	-1.80	-0.95	0.88
roaa_p7	0.38	-0.85	-0.63	-1.66	-0.56	0.43	2.11	1.86	-0.42	0.55	-0.01	-1.85	-1.22	0.88
roaa_p8	0.10	-1.52	-0.91	-1.38	-1.44	0.10	0.89	0.81	-0.37	0.18	-0.18	-1.28	-1.08	0.92
roaa_p9	0.52	-1.53	-1.11	-1.48	-1.59	1.21	2.37	0.15	0.81	1.17	0.36	-1.34	-1.25	-0.02
roaa_p10	-0.17	-1.03	-0.84	-1.64	-1.46	0.34	0.74	0.26	-0.52	-0.15	-0.19	-1.11	-1.23	-1.02
roea_p1	-0.27	-0.71	-0.98	-0.48	-0.48	-0.19	0.58	0.05	-0.67	0.04	-0.99	-0.86	-0.78	-0.40
roea_p2	0.23	-0.61	-0.76	-1.18	-0.61	0.10	0.65	1.59	-0.26	0.48	-0.54	-1.75	-1.46	-0.06
roea_p3	0.32	-0.54	-0.47	-0.66	-1.05	-0.03	0.61	0.97	0.41	0.77	-0.12	-1.49	-1.14	0.01
roea_p4	0.72	-0.69	-0.74	-1.30	-0.66	-0.13	0.52	1.34	0.36	0.98	0.21	-1.33	-0.79	0.97
roea_p5	0.40	-0.56	-0.48	-1.46	-0.71	0.54	0.64	1.83	-0.41	0.43	0.27	-1.90	-1.76	0.14
roea_p6	0.55	-0.70	-0.48	-1.00	-0.82	0.32	1.06	2.64	0.27	0.82	0.11	-2.13	-1.52	0.93
roea_p7	-0.08	-1.17	-0.77	-1.55	-1.21	0.29	1.09	1.36	-0.66	-0.03	-0.43	-1.77	-1.08	0.81
roea_p8	0.10	-1.00	-0.77	-1.44	-1.51	0.22	0.90	1.22	-0.37	0.35	-0.48	-1.87	-1.62	-0.33
roea_p9	0.12	-1.05	-0.72	-1.38	-1.12	0.62	1.43	0.19	-0.16	0.38	-0.14	-1.12	-1.28	-0.53
roea_p10	0.10	-1.49	-0.89	-1.79	-1.90	0.44	1.12	0.47	-0.29	0.29	0.27	-1.27	-1.77	-0.98
sp_p1	-0.17	-1.17	-1.05	-1.48	-0.99	-0.06	0.35	0.71	-0.40	-0.09	-0.39	-1.07	-0.98	-0.63
sp_p2	0.19	-0.81	-0.70	-1.73	-1.12	0.40	1.88	0.64	-0.16	0.34	0.09	-1.30	-1.17	-0.64
sp_p3	0.01	-0.77	-0.65	-1.33	-0.86	0.15	0.42	1.60	-0.55	0.05	-0.20	-2.43	-1.34	0.38

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Table C.10 – continued from previous page

	b.m	tbl	lty	ntis	infl	ltr	corpr	svar	Dpr	Dy	Epr	Der	Dfy	gro_p
sp_p4	0.14	-0.44	-0.44	-1.48	-0.79	-0.07	0.78	1.17	-1.12	-0.09	-0.15	-1.51	-1.21	0.38
sp_p5	-0.30	-0.61	-0.68	-1.68	-1.00	1.45	2.57	1.16	-0.97	-0.27	-1.09	-2.19	-1.35	-0.60
sp_p6	0.50	-0.65	-0.39	-1.57	-1.23	0.30	1.46	1.57	-0.29	0.64	-0.51	-1.98	-1.67	0.12
sp_p7	-0.32	-0.93	-0.71	-0.98	-1.35	0.40	1.98	1.28	-1.01	-0.29	-0.80	-2.23	-1.44	0.64
sp_p8	0.35	-0.82	-0.44	-0.79	-1.25	0.23	0.95	0.67	-0.50	0.43	-0.19	-1.00	-1.32	0.02
sp_p9	-0.34	-0.81	-0.66	-0.60	-1.42	1.43	2.84	1.24	-1.19	-0.20	-0.83	-1.62	-1.76	-0.09
sp_p10	-0.01	-1.06	-0.50	-0.38	-1.13	0.58	2.32	0.72	-0.58	0.31	-0.95	-1.58	-2.02	-0.71
gltnoa_p1	-0.49	-0.93	-0.82	-1.14	-0.79	0.33	0.91	0.48	-1.12	-0.46	-1.04	-1.24	-1.06	-0.78
gltnoa_p2	0.31	-0.50	-0.46	-1.27	-1.41	0.68	1.97	0.26	-0.38	0.62	-0.30	-1.72	-1.73	-0.67
gltnoa_p3	0.47	-0.63	-0.73	-1.87	-0.72	0.43	2.27	0.33	0.10	0.73	0.10	-1.43	-0.88	0.20
gltnoa_p4	0.18	-0.70	-0.67	-1.33	-1.51	0.27	0.85	0.65	0.06	0.47	-0.25	-1.77	-1.28	-0.19
gltnoa_p5	-0.08	-0.50	-0.46	-0.75	-0.86	0.09	0.74	0.13	-0.60	-0.18	-0.28	-1.44	-1.22	0.76
gltnoa_p6	0.08	-0.84	-0.57	-1.62	-0.83	0.12	0.79	1.00	-0.62	-0.02	-0.50	-1.15	-0.90	0.51
gltnoa_p7	0.18	-1.05	-0.97	-1.54	-1.14	0.30	0.62	1.79	-0.15	0.31	0.14	-2.05	-1.20	0.45
gltnoa_p8	0.20	-0.67	-0.61	-1.42	-0.64	1.08	2.32	1.13	-0.26	0.46	-0.40	-1.27	-1.12	-0.26
gltnoa_p9	0.33	-0.75	-0.72	-1.69	-0.90	-0.18	0.71	0.76	-0.35	0.42	-0.12	-1.53	-1.67	0.44
gltnoa_p10	-0.16	-1.40	-1.24	-0.68	-0.91	0.27	1.25	0.26	-0.83	-0.25	-0.46	-1.03	-0.72	-0.24
mom_p1	-0.10	-0.55	-0.74	-0.56	-0.51	1.16	1.57	-1.22	0.14	0.37	-1.28	0.35	0.87	-0.84
mom_p2	0.33	-0.96	-0.81	-0.60	-0.82	1.12	1.70	-0.97	0.80	0.90	-0.99	-0.82	0.18	-1.02
mom_p3	0.39	-0.95	-0.83	-1.05	-1.32	1.19	1.54	-0.61	1.19	1.23	-0.82	-1.45	-0.45	-1.10
mom_p4	0.01	-1.09	-0.80	-0.73	-1.45	1.17	1.07	-0.48	-0.03	0.43	-0.98	-1.83	-1.52	-1.05
mom_p5	0.13	-1.27	-0.91	-1.44	-1.73	0.15	0.93	0.10	0.55	0.79	-0.59	-1.40	-0.77	-0.85
mom_p6	0.31	-0.76	-0.53	-1.49	-0.97	0.97	2.73	0.85	0.32	0.73	-0.42	-1.39	-0.88	0.04
mom_p7	0.13	-0.95	-0.71	-2.39	-1.41	0.60	1.71	1.58	-0.17	0.31	0.16	-1.73	-1.45	0.55
mom_p8	-0.11	-0.75	-0.65	-2.28	-0.76	-0.08	0.81	2.16	-1.57	0.05	-0.52	-1.63	-1.73	0.56
mom_p9	0.14	-0.71	-0.55	-2.29	-0.64	-0.14	1.13	2.18	-1.13	0.22	0.05	-1.36	-1.35	0.93
mom_p10	-0.74	-0.61	-0.61	-0.95	-0.44	-0.34	-0.29	1.96	-2.34	-1.12	0.05	-0.41	-0.88	1.02
indmom_p1	-0.08	-1.06	-1.10	-0.08	-0.89	0.77	1.20	-0.43	-0.20	-0.04	-0.61	-1.26	-0.58	-0.60
indmom_p2	-0.26	-1.20	-1.07	-0.64	-1.07	0.49	0.73	-0.76	-0.41	-0.18	-1.15	-1.91	-0.83	-1.09
indmom_p3	0.03	-0.79	-0.72	-1.23	-1.47	0.45	1.74	-0.54	-0.07	0.30	-0.70	-1.27	-0.83	-1.04
indmom_p4	0.79	-0.52	-0.47	-0.72	-0.88	0.64	2.63	-0.01	0.70	1.50	-0.28	-1.91	-1.21	-1.32
indmom_p5	0.63	-1.27	-1.01	-1.08	-0.98	0.27	2.09	0.69	1.56	1.78	0.22	-0.62	-0.48	-0.30
indmom_p6	-0.05	-0.36	-0.57	-1.45	-0.83	0.65	1.88	-0.04	-1.19	-0.23	-1.04	-1.77	-1.70	-0.29
indmom_p7	-0.08	-1.73	-0.93	-1.43	-2.05	0.33	0.66	1.80	-0.36	-0.12	0.04	-1.46	-1.14	0.32
indmom_p8	-0.46	-0.90	-0.63	-1.68	-1.45	-0.10	-0.53	2.86	-1.38	-0.24	-0.30	-1.95	-2.27	0.66
indmom_p9	1.35	0.20	0.43	-1.83	-1.21	-0.30	-0.02	1.65	0.74	1.49	1.14	-1.20	-1.82	0.95
indmom_p10	-1.63	-0.30	-0.68	-1.09	-0.36	0.01	0.71	0.86	-3.68	-1.96	-1.71	-1.17	-0.44	0.05
valmom_p1	-0.06	-0.87	-0.87	-0.75	-0.95	1.31	1.58	-1.12	0.13	0.32	-0.99	-0.81	0.10	-0.94

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Table C.10 – continued from previous page

	b.m	tbl	lty	ntis	infl	ltr	corpr	svar	Dpr	Dy	Epr	Der	Dfy	gro_p
valmom_p2	0.02	-1.49	-1.35	-0.83	-1.37	0.83	1.37	-0.43	0.56	0.57	-0.62	-1.24	-0.66	-0.84
valmom_p3	0.80	-0.93	-0.54	-1.36	-1.71	0.80	1.68	-0.25	1.54	1.63	0.11	-1.37	-1.50	-0.54
valmom_p4	0.85	-0.72	-0.57	-1.59	-1.13	0.28	1.60	1.02	0.88	1.35	0.35	-1.39	-1.54	-0.45
valmom_p5	-0.25	-1.08	-0.87	-1.32	-0.94	0.02	0.74	0.78	-1.00	-0.42	-0.62	-1.41	-1.02	0.30
valmom_p6	0.06	-1.28	-0.91	-1.68	-0.93	0.12	1.10	0.46	-0.54	-0.08	-0.17	-1.37	-0.71	0.17
valmom_p7	-0.48	-0.58	-0.68	-1.24	-0.79	-0.02	1.04	0.19	-1.72	-0.88	-0.75	-1.06	-0.87	0.33
valmom_p8	-0.26	-0.61	-0.50	-2.40	-0.71	-0.14	0.64	2.66	-1.67	-0.35	-0.34	-1.37	-1.21	1.56
valmom_p9	-0.57	-0.53	-0.48	-1.86	-0.61	0.09	0.95	1.76	-2.17	-0.86	-0.62	-1.56	-1.11	1.90
valmom_p10	-1.05	-0.36	-0.38	-0.90	-0.31	-0.03	0.52	1.53	-2.62	-1.11	-1.23	-1.25	-1.38	1.62
valmomprof_p1	0.46	-0.78	-1.12	-0.48	-0.36	0.53	0.89	-0.45	0.74	0.85	-0.52	-1.55	-0.55	-0.54
valmomprof_p2	-0.14	-0.73	-0.74	-0.69	-0.80	0.48	0.84	-0.39	-0.46	-0.11	-0.66	-1.54	-0.92	-0.59
valmomprof_p3	0.11	-1.26	-0.99	-0.82	-1.38	1.19	1.98	-0.50	0.25	0.55	-0.80	-1.26	-0.83	-0.77
valmomprof_p4	0.30	-0.98	-0.88	-1.40	-0.79	0.65	1.96	-0.87	0.45	0.80	-0.32	-1.21	-0.36	-0.66
valmomprof_p5	0.04	-1.83	-1.61	-1.71	-1.42	1.18	2.72	0.43	0.24	0.38	-0.46	-1.41	-0.64	0.12
valmomprof_p6	0.70	-0.98	-0.74	-2.73	-1.34	0.37	1.67	1.37	0.75	1.31	0.39	-1.63	-0.86	0.42
valmomprof_p7	0.44	-1.01	-0.57	-2.29	-1.21	-0.03	1.05	1.41	0.23	0.63	0.29	-1.27	-1.46	1.22
valmomprof_p8	-0.46	-0.42	-0.37	-1.62	-0.85	-0.01	1.00	1.87	-2.27	-0.61	-0.70	-1.28	-1.89	0.57
valmomprof_p9	-1.19	-0.22	-0.35	-0.91	-0.49	-0.04	0.47	0.85	-3.22	-1.48	-1.31	-1.13	-1.58	0.30
valmomprof_p10	-0.98	-0.46	-0.42	-0.92	-0.63	-0.16	-0.06	1.01	-2.45	-1.39	-1.16	-1.17	-1.43	0.87
shortint_p1	0.21	-0.89	-0.45	-0.35	-0.50	0.12	0.83	0.68	-0.32	0.54	-0.95	-1.22	-1.42	-0.67
shortint_p2	0.21	-1.74	-1.16	-0.98	-0.86	0.44	1.30	1.02	0.22	0.46	-0.47	-1.62	-0.89	-0.41
shortint_p3	0.12	-1.33	-0.90	-1.54	-1.28	0.97	2.69	0.39	-0.15	0.26	-0.48	-1.23	-1.09	-0.27
shortint_p4	0.17	-0.65	-0.48	-1.28	-0.71	0.13	1.51	1.74	-0.53	0.61	-0.55	-1.81	-1.36	-0.05
shortint_p5	-0.20	-1.56	-1.13	-1.66	-1.71	0.51	1.21	1.17	-0.51	-0.22	-0.68	-1.64	-0.86	0.65
shortint_p6	0.14	-1.15	-0.85	-1.18	-1.34	0.59	1.49	1.17	-0.13	0.28	-0.09	-1.43	-0.86	0.49
shortint_p7	-0.24	-0.70	-0.68	-1.28	-0.93	0.13	1.43	0.95	-0.84	0.00	-1.07	-1.66	-1.07	0.86
shortint_p8	0.40	-0.50	-0.63	-1.88	-0.80	1.12	2.69	1.23	-0.35	0.66	-0.01	-1.88	-1.32	-0.09
shortint_p9	0.00	-0.49	-0.68	-1.18	-0.98	0.34	0.95	0.67	-1.04	0.21	-0.11	-1.65	-1.08	0.30
shortint_p10	0.49	0.15	-0.19	-1.33	-1.29	-0.62	0.19	3.40	0.11	0.56	0.94	-1.43	-1.61	-0.01
mom12_p1	-0.29	-0.38	-0.49	-0.44	-0.41	0.73	1.50	-0.87	-0.31	0.01	-1.24	-0.85	-0.41	-0.67
mom12_p2	-0.02	-0.80	-0.76	-0.79	-1.08	1.36	2.33	-1.09	0.07	0.24	-1.18	-1.36	-0.68	-0.80
mom12_p3	0.23	-0.81	-0.72	-1.14	-1.45	1.23	1.46	-0.98	0.63	0.84	-1.23	-1.53	-0.61	-1.27
mom12_p4	-0.10	-0.89	-0.69	-1.18	-1.55	1.21	1.55	-0.61	-0.32	0.07	-1.05	-2.26	-1.39	-0.83
mom12_p5	-0.15	-0.81	-0.64	-0.96	-2.07	0.34	0.59	0.05	-0.16	0.12	-1.13	-1.82	-0.89	-1.07
mom12_p6	0.07	-0.92	-0.66	-1.59	-1.09	0.40	0.88	0.93	-0.34	0.67	-1.00	-1.35	-1.40	-0.70
mom12_p7	0.24	-0.73	-0.53	-1.55	-0.81	0.52	1.47	-0.27	-0.15	0.80	-0.23	-1.33	-1.42	-0.40
mom12_p8	0.17	-0.75	-0.54	-1.60	-0.40	0.03	1.08	2.62	-0.77	0.46	0.34	-1.35	-1.53	0.67
mom12_p9	1.00	-0.21	-0.16	-1.27	0.06	0.21	1.76	3.44	-0.59	0.96	1.16	-1.59	-1.43	0.88

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Table C.10 – continued from previous page

	b.m	tbl	lty	ntis	infl	ltr	corpr	svar	Dpr	Dy	Epr	Der	Dfy	gro_p
mom12_p10	-0.04	-1.14	-1.00	-0.53	-0.45	-0.27	0.21	1.83	-1.09	-0.37	0.23	-0.86	-0.65	0.65
momrev_p1	-0.03	-1.17	-1.12	-0.81	-0.45	-0.12	0.85	1.05	-0.77	-0.20	-0.51	-1.10	-0.45	0.40
momrev_p2	-0.35	-0.88	-0.84	-1.12	-0.25	0.01	1.24	1.03	-1.32	-0.42	-0.43	-1.32	-0.65	1.07
momrev_p3	-0.30	-0.59	-0.63	-1.67	-0.67	0.26	1.90	1.79	-1.46	-0.22	0.16	-1.15	-1.94	0.07
momrev_p4	0.29	-0.68	-0.61	-1.68	-0.87	0.03	1.08	1.04	-0.06	0.58	-0.16	-1.43	-1.38	-0.35
momrev_p5	0.44	-0.04	-0.18	-1.37	-1.09	0.11	0.57	2.11	-0.74	0.33	0.34	-2.07	-2.60	-0.93
momrev_p6	0.00	-1.16	-0.92	-1.25	-1.53	0.24	0.63	1.07	-0.31	0.11	-0.58	-2.10	-1.90	-0.10
momrev_p7	0.15	-0.56	-0.67	-1.36	-1.20	0.42	0.67	-0.12	-0.15	0.67	-1.11	-1.81	-1.61	-1.36
momrev_p8	0.07	-0.72	-0.65	-0.93	-2.03	0.99	0.70	-0.67	0.00	0.24	-0.83	-1.72	-1.17	-0.93
momrev_p9	0.19	-1.06	-0.91	-0.62	-1.63	0.25	-0.02	0.65	0.05	0.30	-0.76	-1.88	-1.21	-0.36
momrev_p10	-0.32	-0.75	-0.70	-0.20	-1.57	0.36	1.07	0.31	-0.98	-0.37	-0.92	-1.83	-1.52	-0.35
lrrev_p1	-0.14	-1.60	-1.36	-1.60	-0.83	0.40	1.55	0.86	-0.67	-0.16	-0.45	-1.35	-0.79	-0.18
lrrev_p2	-0.09	-1.18	-0.99	-2.25	-0.60	0.23	1.41	0.21	-1.16	-0.13	0.37	-1.05	-0.94	0.97
lrrev_p3	0.29	-1.15	-0.79	-1.67	-0.94	0.39	1.86	0.70	-0.19	0.63	-0.10	-1.57	-1.18	-0.61
lrrev_p4	0.33	-1.10	-0.64	-1.97	-1.50	0.17	1.09	0.30	-0.17	0.64	0.03	-1.59	-1.28	0.50
lrrev_p5	-0.16	-0.46	-0.51	-1.12	-1.01	0.10	0.70	1.56	-1.07	-0.27	-0.33	-1.38	-1.45	0.10
lrrev_p6	-0.04	-1.08	-0.58	-0.87	-1.49	0.52	1.43	2.10	-0.64	0.00	-0.70	-2.08	-1.49	0.16
lrrev_p7	0.30	-0.47	-0.43	-0.93	-1.43	0.40	1.02	1.46	-0.20	0.76	-0.37	-1.94	-1.86	-0.68
lrrev_p8	-0.39	-0.54	-0.36	-0.35	-1.32	0.21	1.03	1.26	-1.13	-0.25	-0.86	-1.24	-2.32	-0.49
lrrev_p9	-0.39	-0.72	-0.72	0.16	-0.80	0.36	0.77	0.06	-0.83	-0.24	-0.85	-1.23	-1.35	-0.65
lrrev_p10	-0.30	-0.87	-0.85	-0.02	-0.96	0.47	1.55	0.02	-0.59	-0.21	-0.72	-0.42	-0.75	-0.82
valuem_p1	-0.01	-1.51	-1.17	-2.07	-1.03	-0.06	0.56	1.00	-0.35	-0.03	0.02	-0.98	-1.13	-0.48
valuem_p2	0.04	-1.25	-0.77	-1.93	-1.20	0.10	0.52	0.02	-0.44	0.39	-0.03	-1.06	-1.70	-0.56
valuem_p3	-0.19	-1.23	-0.99	-1.36	-1.02	0.67	1.65	0.51	-0.74	0.09	-0.56	-1.30	-0.90	-0.15
valuem_p4	0.00	-0.90	-0.99	-1.67	-0.57	0.71	1.48	0.78	-0.47	0.22	-0.31	-1.57	-0.96	0.68
valuem_p5	0.16	-0.74	-0.83	-1.21	-0.41	0.37	0.84	1.38	-0.51	0.21	0.14	-1.57	-1.17	0.63
valuem_p6	0.26	-0.52	-0.66	-1.09	-0.86	1.03	1.75	0.34	-0.28	0.23	-0.01	-1.83	-1.10	0.53
valuem_p7	0.01	-0.74	-0.77	-1.23	-1.71	0.56	1.69	-0.03	-0.01	0.31	-0.74	-1.44	-0.78	-0.07
valuem_p8	0.76	-0.32	-0.32	-0.98	-0.84	1.20	2.26	-0.25	0.98	1.28	-0.20	-1.98	-0.80	-0.34
valuem_p9	0.62	-0.41	-0.48	-0.77	-0.98	1.26	2.29	-1.38	0.76	1.05	-1.23	-1.98	-0.10	-1.28
valuem_p10	0.13	-0.67	-0.55	-0.60	-0.98	1.17	1.85	-1.85	0.33	0.66	-1.46	-1.36	-0.24	-0.99
nissm_p1	0.13	-0.75	-0.72	-1.00	-0.87	-0.35	-0.27	2.23	-0.09	0.49	-0.74	-2.23	-1.54	-1.06
nissm_p2	-0.13	-0.51	-0.64	-0.91	-0.64	0.06	0.50	0.74	-0.86	-0.20	-0.65	-1.77	-1.15	-0.38
nissm_p3	-0.44	-0.81	-0.69	-0.88	-0.81	0.05	1.01	0.61	-1.33	-0.53	-0.77	-1.10	-0.89	-0.15
nissm_p4	0.23	-1.15	-0.70	-1.23	-1.34	0.22	0.96	1.53	-0.10	0.43	-0.19	-1.42	-1.54	-0.38
nissm_p5	0.22	-0.61	-0.84	-1.36	-0.94	1.09	1.77	0.10	-0.06	0.45	-0.31	-1.66	-1.05	-0.49
nissm_p6	-0.04	-1.03	-0.72	-0.87	-0.91	0.51	1.17	0.14	-0.81	-0.07	-0.52	-1.27	-1.32	-0.01
nissm_p7	0.47	-1.17	-0.88	-1.37	-1.09	0.57	1.69	1.30	0.17	0.70	0.54	-1.41	-1.36	0.37

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Table C.10 – continued from previous page

	b.m	tbl	lty	ntis	infl	ltr	corpr	svar	Dpr	Dy	Epr	Der	Dfy	gro_p
nissm_p8	-0.05	-1.28	-1.06	-1.45	-1.64	0.41	0.96	0.73	-0.60	-0.01	-0.30	-1.37	-1.28	0.40
nissm_p9	0.15	0.03	-0.31	-2.30	-0.92	0.47	1.65	1.20	-0.58	0.36	0.19	-1.75	-2.05	0.23
nissm_p10	0.17	-1.09	-0.81	-1.27	-1.34	0.83	2.89	0.69	-0.47	0.12	0.04	-1.24	-1.07	0.68
sue_p1	0.06	-0.55	-0.69	-0.72	-0.89	0.36	0.23	0.40	0.15	0.29	-0.81	-2.08	-1.40	0.38
sue_p2	-0.02	-0.62	-0.58	-0.95	-1.17	-0.19	-0.52	1.36	-0.27	0.42	-0.81	-1.68	-1.68	-0.01
sue_p3	0.01	-1.15	-0.73	-1.16	-1.72	0.01	-0.55	2.74	0.03	0.30	-0.47	-2.42	-1.25	0.49
sue_p4	-0.26	-1.03	-0.64	-0.89	-2.31	0.45	-0.11	1.45	-0.84	-0.40	-0.57	-2.20	-1.22	0.25
sue_p5	-0.38	-1.01	-0.64	-1.41	-1.16	0.41	0.95	0.39	-1.03	-0.40	-0.82	-1.59	-0.84	0.72
sue_p6	-0.23	-1.13	-0.78	-1.38	-1.08	0.42	0.33	0.62	-0.58	-0.28	-0.63	-1.71	-0.90	0.57
sue_p7	-0.48	-0.35	-0.51	-1.13	-0.43	0.12	1.13	0.22	-1.43	-0.27	-1.25	-1.42	-1.00	-0.42
sue_p8	0.04	-0.96	-0.78	-1.02	-1.28	0.09	1.48	0.89	-0.61	0.05	0.10	-1.02	-0.67	0.46
sue_p9	-0.03	-0.85	-0.91	-2.14	-0.69	0.34	1.25	0.59	-0.37	0.10	0.24	-1.07	-0.80	0.13
sue_p10	0.69	-0.54	-0.75	-1.37	-0.52	-0.22	0.70	2.19	0.54	0.76	0.05	-1.02	-0.91	0.95
roe_p1	-0.27	-0.59	-0.63	-0.38	-0.61	0.01	0.94	0.49	-0.72	-0.25	-0.78	-1.42	-0.95	0.19
roe_p2	0.44	-0.74	-0.67	-0.57	-0.77	0.51	1.33	1.40	0.47	0.95	-0.62	-1.87	-1.39	-0.40
roe_p3	-0.24	-0.70	-0.63	-1.33	-1.22	0.08	0.14	-0.19	-0.67	-0.01	-1.42	-1.96	-1.77	-0.74
roe_p4	0.13	-0.75	-0.77	-1.36	-1.57	0.20	-0.20	0.66	-0.09	0.31	-0.67	-2.51	-1.24	-0.03
roe_p5	0.31	-0.93	-0.72	-1.42	-1.06	-0.23	-0.09	1.12	0.41	0.63	0.42	-1.22	-0.82	0.22
roe_p6	0.11	-0.45	-0.51	-0.76	-0.56	-0.22	0.01	1.57	-0.61	0.45	-0.72	-1.62	-1.33	0.75
roe_p7	0.06	-0.85	-0.63	-0.96	-0.97	0.34	0.57	1.66	-0.66	0.07	-0.46	-2.32	-1.64	-0.24
roe_p8	0.13	-0.94	-0.66	-1.24	-0.90	0.28	1.67	0.88	-0.54	0.38	-0.22	-1.14	-1.33	-0.21
roe_p9	0.03	-1.25	-0.65	-1.64	-1.41	0.60	2.15	1.24	-0.51	0.17	0.08	-1.12	-1.13	0.57
roe_p10	0.35	-1.10	-1.11	-2.31	-1.14	0.22	0.77	0.34	0.10	0.49	0.68	-1.20	-0.92	-0.13
rome_p1	-0.19	-0.92	-0.78	-0.16	-0.75	0.11	1.34	0.59	-0.56	-0.13	-0.82	-1.43	-1.09	0.20
rome_p2	-0.27	-0.76	-0.73	-0.69	-0.60	-0.09	0.48	0.29	-0.75	-0.18	-1.08	-1.54	-1.22	-0.11
rome_p3	-0.38	-0.86	-0.71	-0.97	-0.81	0.12	-0.30	0.08	-0.83	-0.18	-1.26	-1.80	-1.54	-0.94
rome_p4	0.05	-1.07	-0.86	-1.95	-0.92	0.03	0.89	1.19	-0.48	0.26	-0.47	-1.60	-1.46	-1.53
rome_p5	0.48	-0.93	-0.78	-2.77	-0.73	0.75	1.30	1.46	-0.01	0.71	0.52	-1.37	-1.85	-0.36
rome_p6	-0.09	-1.45	-1.04	-2.43	-1.40	0.45	1.22	1.49	-0.55	-0.10	-0.08	-1.56	-0.88	0.41
rome_p7	0.29	-0.24	-0.54	-1.26	-0.76	0.39	1.79	1.66	-0.15	0.43	1.09	-1.14	-0.87	1.02
rome_p8	0.34	-0.34	-0.43	-0.71	-0.94	0.87	2.82	1.34	-0.36	0.35	0.10	-1.68	-0.98	0.29
rome_p9	-0.24	-0.18	-0.43	-0.58	-0.90	1.20	2.93	-0.09	-1.22	-0.03	-0.82	-1.54	-1.00	-0.20
rome_p10	0.04	-0.55	-0.42	-0.42	-1.06	0.07	2.13	0.16	-0.78	-0.08	-0.77	-1.58	-1.14	-0.20
roa_p1	-0.33	-0.53	-0.63	-0.50	-0.44	-0.15	0.64	0.19	-0.85	-0.42	-0.79	-1.18	-0.76	-0.07
roa_p2	0.02	-0.31	-0.37	0.23	-0.97	0.38	1.76	1.81	-0.45	0.40	-0.83	-1.83	-1.73	0.47
roa_p3	-0.23	-0.65	-0.59	-0.85	-1.12	-0.30	-1.01	1.06	-0.63	-0.14	-1.01	-2.88	-2.04	-1.13
roa_p4	-0.11	-0.60	-0.56	-1.13	-1.42	0.37	0.87	0.92	-0.61	-0.01	-1.11	-2.03	-1.84	-0.43
roa_p5	0.10	-0.79	-0.82	-1.87	-1.39	-0.14	0.05	0.52	-0.28	0.21	-0.47	-2.06	-1.16	-0.59

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Table C.10 – continued from previous page

	b.m	tbl	lty	ntis	infl	ltr	corpr	svar	Dpr	Dy	Epr	Der	Dfy	gro_p
roa_p6	0.86	-0.46	-0.44	-1.33	-0.58	0.08	1.12	1.08	0.36	1.26	0.27	-1.60	-0.90	0.44
roa_p7	0.81	-0.99	-0.85	-1.57	-0.38	0.29	1.34	0.77	0.41	1.03	0.33	-1.65	-0.88	0.10
roa_p8	0.07	-1.04	-0.83	-0.88	-0.98	0.54	1.36	0.39	-0.46	0.51	-0.70	-1.02	-1.04	-0.03
roa_p9	-0.02	-1.31	-0.97	-1.71	-1.14	0.42	1.61	1.05	-0.45	0.04	0.09	-1.28	-1.13	1.05
roa_p10	0.02	-1.30	-0.99	-2.02	-1.50	0.28	0.63	0.58	-0.27	0.00	0.32	-0.99	-0.97	-0.06
strev_p1	-0.04	-0.85	-1.06	-0.44	-0.44	-0.09	-0.05	0.37	-0.61	-0.06	-0.80	-1.61	-0.74	-0.12
strev_p2	0.94	-0.45	-0.51	-1.19	-0.65	-0.01	-0.02	-0.69	0.94	1.48	0.05	-2.10	-1.03	-0.80
strev_p3	0.78	-0.34	-0.47	-0.78	-0.49	0.04	-0.07	0.64	0.47	0.96	-0.14	-2.03	-1.11	-0.13
strev_p4	0.22	-0.75	-0.86	-1.68	-0.86	0.51	0.89	0.51	0.46	0.76	-0.58	-1.54	-1.27	-0.09
strev_p5	0.51	-1.63	-0.85	-1.84	-1.53	0.71	1.52	1.31	0.42	0.81	0.79	-1.18	-0.92	0.74
strev_p6	-0.02	-0.56	-0.55	-1.57	-1.47	1.21	2.65	1.71	-0.69	0.18	-0.21	-1.40	-1.94	0.13
strev_p7	-0.24	-0.98	-0.80	-1.29	-1.36	0.83	1.94	1.64	-0.89	-0.30	-0.17	-1.07	-1.26	0.16
strev_p8	-0.08	-0.67	-0.56	-0.95	-1.80	0.29	2.11	1.90	-0.72	-0.02	-0.07	-1.28	-1.46	0.42
strev_p9	-0.41	-0.53	-0.59	-0.78	-0.88	0.20	2.37	1.27	-1.33	-0.27	-0.88	-1.70	-1.34	-0.62
strev_p10	-0.27	-0.66	-0.70	-0.43	-0.76	0.62	1.70	-0.09	-0.98	-0.15	-1.28	-1.95	-1.10	-0.44
ivol_p1	-0.56	-0.30	-0.53	-0.24	-0.21	-0.01	0.54	-0.49	-1.15	-0.82	-1.11	-1.21	-0.55	-0.51
ivol_p2	-0.41	-1.00	-1.01	-0.13	-0.56	-0.03	0.20	-0.06	-0.93	-0.42	-1.30	-1.50	-1.00	-0.52
ivol_p3	-0.13	-0.93	-0.97	-0.54	-0.66	0.52	1.30	0.14	-0.62	0.24	-1.46	-1.74	-0.84	-0.86
ivol_p4	0.66	-1.13	-0.99	-0.61	-0.80	0.63	1.41	-0.43	0.43	1.22	-0.62	-1.50	-0.67	-0.78
ivol_p5	-0.18	-1.00	-0.88	-0.60	-0.75	0.64	2.31	1.72	-1.14	-0.04	-1.03	-1.63	-1.38	-0.14
ivol_p6	0.56	-0.97	-0.80	-1.12	-1.19	0.56	1.47	2.11	0.19	0.93	-0.19	-1.87	-1.22	-0.23
ivol_p7	0.02	-0.94	-0.81	-1.28	-0.99	0.24	1.01	1.75	-0.88	0.11	-0.11	-1.85	-1.40	0.80
ivol_p8	0.43	-0.75	-0.66	-1.89	-0.74	0.25	1.48	0.63	0.22	0.76	-0.26	-1.48	-1.04	-0.05
ivol_p9	0.26	-0.30	-0.40	-1.92	-0.83	0.28	1.40	0.55	0.07	0.47	0.25	-1.37	-1.29	0.94
ivol_p10	0.24	-0.11	-0.21	-2.19	-1.49	-0.06	0.35	1.29	-0.27	0.31	0.77	-1.20	-1.88	-0.42
betaarb_p1	-0.02	-1.43	-1.26	-0.54	-0.59	-0.11	0.79	0.37	0.10	0.37	-1.03	-1.17	-0.70	-0.32
betaarb_p2	-0.05	-1.30	-1.06	-0.94	-0.83	-0.31	-0.12	2.17	-0.22	0.18	-0.86	-2.37	-1.26	0.15
betaarb_p3	0.11	-1.07	-0.95	-1.46	-0.72	0.30	1.97	2.54	0.05	0.48	-0.34	-2.04	-1.13	0.65
betaarb_p4	0.11	-0.94	-0.67	-2.10	-1.20	0.25	1.00	1.57	0.04	0.49	-1.03	-2.42	-1.59	-0.37
betaarb_p5	0.59	-0.43	-0.48	-1.40	-0.46	0.09	1.26	0.52	0.50	1.07	-0.61	-2.21	-1.22	0.24
betaarb_p6	0.55	-0.54	-0.50	-1.47	-0.56	1.36	2.78	0.99	-0.16	0.74	-0.44	-1.88	-1.35	-0.57
betaarb_p7	0.48	-0.07	-0.38	-1.62	-0.82	1.15	2.33	1.60	-0.83	0.37	0.19	-1.80	-2.18	-0.46
betaarb_p8	0.75	-0.31	-0.23	-1.22	-1.81	0.89	2.60	1.08	0.07	0.85	0.22	-1.39	-2.01	-2.05
betaarb_p9	0.18	-0.04	-0.39	-1.20	-1.11	1.68	2.92	0.80	-1.15	-0.15	0.11	-1.31	-1.70	-0.53
betaarb_p10	0.49	0.22	-0.10	-1.20	-1.94	-0.54	0.19	1.43	-0.98	0.43	0.85	-1.10	-2.68	-1.87
season_p1	-0.96	-0.54	-0.73	-0.45	-0.37	0.42	1.34	-0.03	-2.05	-0.72	-1.90	-1.81	-1.50	-0.98
season_p2	-0.30	-0.56	-0.96	-0.80	-0.67	0.73	1.48	0.19	-1.49	0.15	-0.79	-2.08	-2.06	-0.57
season_p3	-0.01	-0.55	-0.60	-1.03	-0.82	0.57	1.21	0.50	-0.55	0.46	-0.97	-2.20	-2.00	-0.29

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Table C.10 – continued from previous page

	b.m	tbl	lty	ntis	infl	ltr	corpr	svar	Dpr	Dy	Epr	Der	Dfy	gro_p
season_p4	-0.05	-0.65	-0.63	-0.98	-1.12	1.00	2.27	1.76	-0.64	0.27	-0.26	-1.42	-1.87	0.39
season_p5	-0.04	-0.50	-0.45	-1.10	-1.24	0.45	1.45	1.20	-0.92	0.12	-0.23	-1.63	-1.90	0.13
season_p6	0.61	-0.74	-0.66	-1.40	-1.43	0.19	1.28	0.94	0.41	1.10	0.88	-1.26	-1.22	0.64
season_p7	0.10	-1.04	-0.82	-1.92	-1.28	0.21	0.42	0.82	-0.03	0.36	-0.38	-1.75	-1.10	0.13
season_p8	0.33	-1.06	-0.96	-1.42	-1.12	0.14	1.06	1.01	0.36	0.85	-0.04	-1.01	-0.72	-0.12
season_p9	0.23	-2.31	-2.14	-1.82	-1.43	-0.13	0.48	1.70	0.41	0.55	0.29	-1.45	-0.69	0.52
season_p10	0.10	-2.15	-2.22	-1.06	-0.86	0.12	0.55	1.17	0.08	0.34	0.01	-1.08	-0.36	0.49
indrrev_p1	-0.32	-0.74	-0.83	-0.51	-0.48	-0.05	-0.26	0.52	-1.12	-0.55	-1.05	-1.79	-0.89	-0.26
indrrev_p2	-0.11	-1.22	-1.01	-1.07	-0.90	-0.06	-0.02	-0.88	-0.38	0.13	-1.02	-1.45	-0.61	-0.72
indrrev_p3	-0.14	-0.98	-0.99	-1.30	-0.60	-0.01	0.08	0.75	-0.50	0.02	-0.56	-1.72	-0.98	-0.26
indrrev_p4	0.37	-0.55	-0.73	-1.57	-0.76	0.31	1.14	2.83	-0.15	0.50	0.52	-1.80	-1.54	0.43
indrrev_p5	0.41	-1.16	-0.72	-1.94	-1.52	0.60	1.21	0.73	0.62	0.73	0.19	-1.25	-1.04	0.42
indrrev_p6	0.06	-0.73	-0.56	-1.86	-1.64	0.65	1.55	0.16	-0.15	0.54	-0.34	-1.41	-1.43	0.05
indrrev_p7	0.10	-0.32	-0.35	-1.36	-1.06	0.63	1.94	1.01	-0.46	0.20	-0.13	-1.32	-1.48	-0.33
indrrev_p8	0.43	-0.53	-0.28	-0.82	-1.24	0.06	1.46	2.18	-0.24	0.79	0.25	-1.21	-1.51	0.35
indrrev_p9	0.53	-0.56	-0.48	-0.67	-0.90	0.55	2.21	0.71	0.27	1.05	-0.58	-1.48	-1.23	-0.62
indrrev_p10	0.39	-0.66	-0.68	-0.28	-0.73	0.98	2.32	-0.44	-0.13	0.57	-0.68	-1.27	-0.67	-0.47
indrrevlv_p1	-0.10	-0.86	-0.74	-0.90	-0.86	0.03	0.46	1.38	-0.66	-0.09	-0.35	-1.40	-0.77	0.19
indrrevlv_p2	-0.26	-1.15	-0.83	-1.64	-0.85	-0.17	0.18	-1.26	-0.73	-0.34	-0.74	-1.72	-0.70	0.06
indrrevlv_p3	0.29	-0.63	-0.90	-1.90	-0.60	0.36	0.43	1.55	0.15	0.42	1.22	-1.41	-1.28	-0.08
indrrevlv_p4	-0.10	-0.29	-0.55	-1.78	-0.44	0.54	1.41	1.38	-1.25	-0.36	-0.36	-1.86	-1.72	0.05
indrrevlv_p5	0.18	-0.33	-0.43	-1.68	-1.14	0.19	1.02	2.45	-0.41	0.07	0.15	-1.36	-1.36	0.36
indrrevlv_p6	-0.03	-1.08	-0.68	-2.62	-2.94	0.66	1.70	0.83	0.58	0.76	0.13	-1.43	-1.30	0.40
indrrevlv_p7	0.50	-0.01	-0.12	-1.77	-0.75	0.46	1.05	1.08	0.14	0.70	0.69	-1.33	-1.35	0.67
indrrevlv_p8	0.43	0.53	0.39	-1.47	-1.18	0.04	1.47	0.65	-0.68	0.50	0.35	-1.21	-2.07	0.02
indrrevlv_p9	0.71	-0.29	-0.21	-1.19	-1.07	0.30	1.55	0.02	0.45	1.61	-0.30	-0.94	-0.78	-0.56
indrrevlv_p10	1.24	-0.07	0.19	-0.49	-1.14	0.35	3.01	2.11	0.77	1.62	0.17	-1.40	-1.53	-0.53
indmomrev_p1	-0.31	-0.83	-0.74	-0.85	-1.00	0.11	0.68	0.71	-0.86	-0.42	-0.66	-2.07	-1.13	-0.82
indmomrev_p2	0.04	-1.37	-0.95	-0.99	-1.37	0.13	0.73	-0.97	0.54	0.48	-0.46	-1.58	-0.45	-0.87
indmomrev_p3	0.11	-0.60	-0.63	-1.51	-0.69	0.23	0.60	-0.38	-0.02	0.18	-0.51	-1.20	-0.79	-0.80
indmomrev_p4	-0.06	-0.63	-0.73	-1.43	-1.10	1.05	3.09	0.59	-0.23	0.02	-0.50	-1.33	-1.25	-0.45
indmomrev_p5	0.26	-0.46	-0.30	-1.39	-1.75	0.70	1.59	1.00	-0.05	0.44	0.17	-1.52	-1.78	0.49
indmomrev_p6	0.14	-0.87	-0.58	-2.27	-1.19	0.01	1.01	2.10	-0.22	0.35	0.13	-1.36	-1.23	1.19
indmomrev_p7	-0.14	-0.04	-0.39	-1.88	-1.13	0.03	0.94	1.43	-1.21	-0.05	-0.46	-1.50	-2.24	-0.30
indmomrev_p8	0.30	0.08	-0.04	-1.89	-1.37	0.10	0.93	2.26	-0.50	0.49	0.69	-1.35	-1.99	0.86
indmomrev_p9	0.54	0.93	0.71	-2.27	-0.81	0.35	0.44	1.70	-0.66	0.78	0.51	-1.72	-1.69	1.19
indmomrev_p10	0.75	-0.09	0.17	-1.73	-0.75	0.42	2.23	0.46	-0.51	0.76	0.36	-1.22	-1.22	-0.11
ciss_p1	-0.32	-0.72	-0.74	-0.43	-0.55	0.49	1.70	0.62	-1.16	-0.10	-0.83	-1.38	-1.27	-0.60

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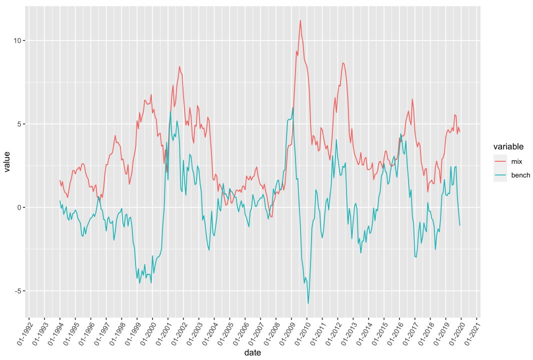
Table C.10 – continued from previous page

	b.m	tbl	lty	ntis	infl	ltr	corpr	svar	Dpr	Dy	Epr	Der	Dfy	gro_p
ciss_p2	0.06	-1.10	-0.91	-0.90	-0.80	0.43	0.83	1.46	-0.30	0.17	-0.48	-1.89	-1.46	-0.53
ciss_p3	-0.13	-0.76	-0.71	-0.59	-0.62	0.16	0.89	0.81	-0.95	-0.03	-0.50	-1.31	-1.05	-0.14
ciss_p4	-0.09	-0.67	-0.69	-0.70	-0.96	0.03	1.17	0.92	-0.63	0.14	-0.56	-1.34	-1.16	0.32
ciss_p5	-0.20	-0.73	-0.70	-1.28	-1.00	0.00	1.15	0.16	-0.84	-0.11	-0.71	-1.38	-0.85	-0.25
ciss_p6	-0.06	-0.63	-0.60	-1.03	-1.11	0.06	0.70	0.54	-0.81	0.00	-0.10	-1.69	-1.67	-0.33
ciss_p7	0.32	-0.94	-0.94	-1.78	-1.25	0.63	0.65	1.32	0.03	0.63	0.14	-1.75	-1.36	-0.13
ciss_p8	0.09	-0.63	-0.33	-2.24	-1.47	-0.01	-0.01	1.43	-0.17	0.36	-0.20	-2.06	-2.08	0.24
ciss_p9	0.38	-0.54	-0.44	-2.16	-1.54	0.19	0.95	0.02	-0.04	0.48	-0.33	-1.18	-1.20	0.00
ciss_p10	0.74	-1.41	-0.82	-1.83	-2.34	0.76	2.80	3.20	0.36	1.09	1.15	-1.15	-1.41	1.27
price_p1	-0.61	-0.55	-0.82	-0.37	-0.27	-0.08	0.58	-0.67	-1.02	-0.65	-1.18	-0.54	0.02	-0.70
price_p2	-0.32	-0.61	-0.68	-0.45	-0.57	0.60	0.96	-0.57	-0.67	-0.06	-1.52	-1.56	-0.60	-0.93
price_p3	-0.31	-0.65	-0.65	-0.47	-0.98	0.41	0.90	-0.53	-0.80	-0.16	-1.29	-1.58	-1.19	-1.38
price_p4	0.07	-0.64	-0.66	-0.69	-1.21	0.59	1.00	-0.23	-0.18	0.35	-0.87	-1.36	-1.00	-1.08
price_p5	0.25	-0.83	-0.74	-0.87	-1.33	0.61	0.44	-0.14	0.13	0.49	-0.53	-1.76	-1.38	-1.10
price_p6	0.54	-0.50	-0.50	-0.86	-1.03	0.42	1.17	0.40	0.12	0.77	-0.40	-1.37	-1.27	-0.82
price_p7	0.42	-0.76	-0.68	-1.35	-1.26	0.89	1.68	0.49	0.00	0.58	-0.15	-1.67	-1.23	-0.15
price_p8	0.65	-0.67	-0.51	-1.26	-1.17	0.36	0.94	1.51	0.44	0.96	0.27	-1.79	-1.93	-0.30
price_p9	0.18	-0.97	-0.76	-1.83	-0.96	0.85	2.20	1.09	-0.34	0.48	0.00	-1.53	-1.23	0.63
price_p10	0.08	-0.97	-0.74	-2.02	-0.98	-0.15	0.40	1.53	-0.43	0.19	0.63	-1.04	-1.04	1.12
shvol_p1	-0.38	-0.85	-0.83	-0.19	-0.50	0.19	0.77	0.05	-0.96	-0.36	-1.09	-0.88	-0.57	-0.50
shvol_p2	-0.23	-1.13	-1.05	-0.80	-0.67	0.11	0.78	0.95	-0.87	-0.13	-1.04	-1.41	-0.94	-0.23
shvol_p3	0.07	-0.80	-0.75	-1.10	-0.41	-0.06	0.56	1.68	-0.35	0.58	-0.92	-1.94	-1.17	0.70
shvol_p4	0.34	-1.00	-0.78	-1.09	-0.78	0.73	1.63	2.27	-0.16	0.38	0.42	-1.65	-1.14	0.74
shvol_p5	0.19	-0.69	-0.64	-1.08	-0.76	0.26	1.23	0.64	-0.46	0.38	-0.17	-1.45	-1.26	-0.03
shvol_p6	0.16	-0.48	-0.61	-1.75	-0.65	0.42	1.84	2.03	-0.62	0.33	0.05	-1.76	-1.47	0.46
shvol_p7	0.42	-0.58	-0.57	-2.38	-1.03	0.68	2.19	0.95	0.15	0.65	0.36	-1.40	-1.79	0.08
shvol_p8	0.19	-1.66	-1.08	-2.25	-1.89	0.04	1.07	0.54	0.32	0.50	0.34	-1.43	-0.73	0.61
shvol_p9	0.12	-0.73	-0.64	-1.44	-1.67	0.00	0.21	-0.04	-0.62	0.03	0.40	-1.20	-1.60	0.78
shvol_p10	0.37	-0.18	-0.09	-1.44	-2.42	-0.08	-0.02	1.45	0.16	0.78	-0.07	-1.80	-2.02	-0.90

C.2 Figures



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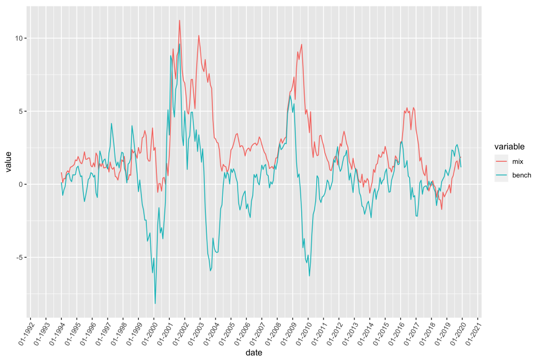

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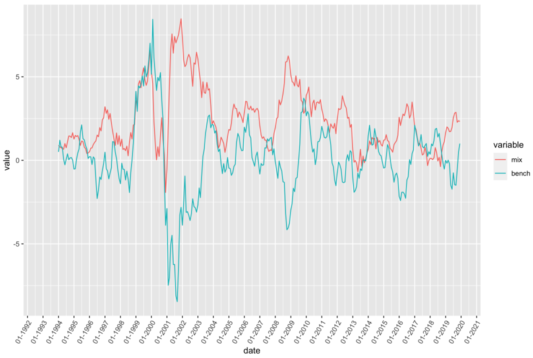

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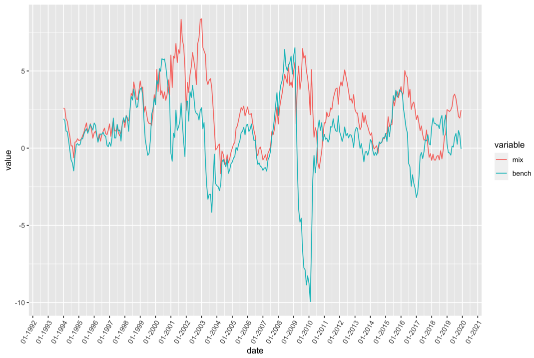
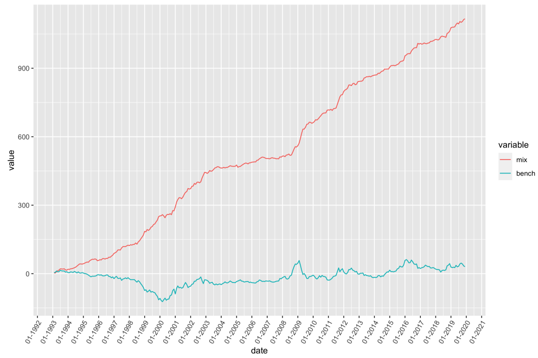


(d) Mom12

Figure C.1: First four highest long minus short mean returns.

In these figures, we plot the time series of the deciles-based and benchmark strategies returns. **Deciles-based strategy:** Go long the decile with the highest expected return and go short the decile with the lowest expected return. **Benchmark strategy:** Go long the first (last) decile and go short the last (first) decile based on which extreme decile has the highest average return. See section 3.2.1 in the main text.

C.3 Additional figures



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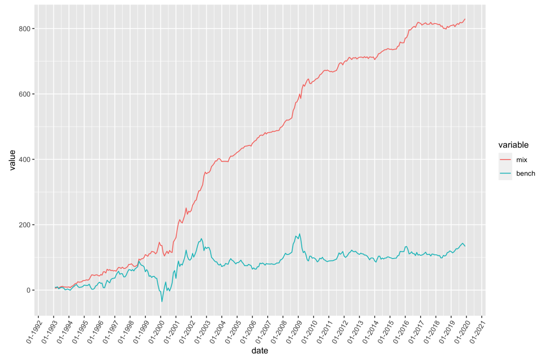

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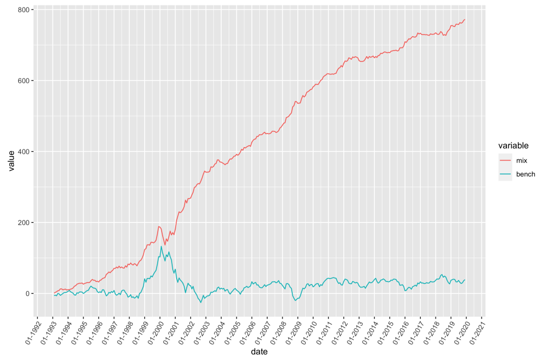

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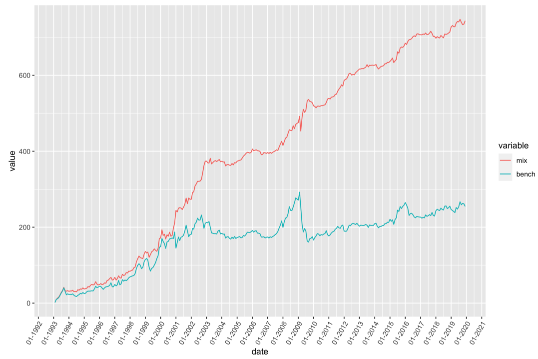


(d) Mom12

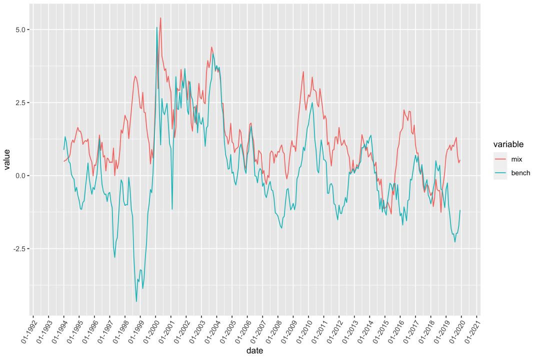
Figure C.2: Cumulative returns of the first four highest long minus short mean returns.

In these figures, we plot the cumulative returns' time series of the deciles-based and benchmark strategies returns. **Deciles-based strategy:** Go long the decile with the highest expected return and go short the decile with the lowest expected return. **Benchmark strategy:** Go long the first (last) decile and go short the last (first) decile based on which extreme decile has the highest average return. See section 3.2.1 in the main text.

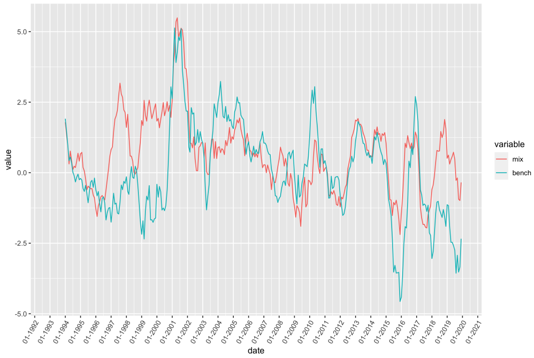
Figure C.3: Long minus short returns of the strategies.

In these figures, we plot the time series of the deciles-based and benchmark strategies returns. **Deciles-based strategy:** Go long the decile with the highest expected return and go short the decile with the lowest expected return. **Benchmark strategy:** Go long the first (last) decile and go short the last (first) decile based on which extreme decile has the highest average return. See section 3.2.1 in the main text.

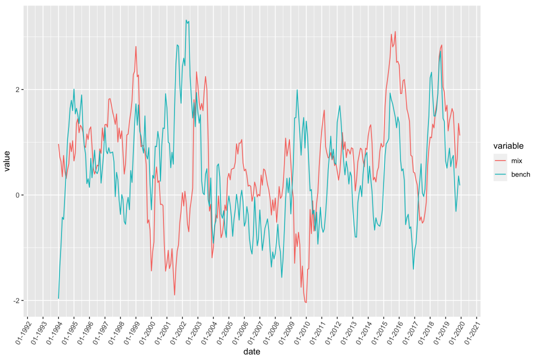
(a) Size



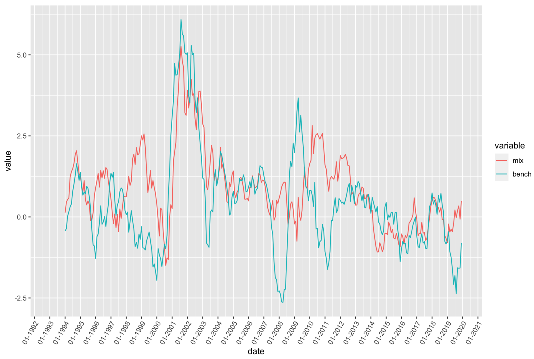
(b) Value



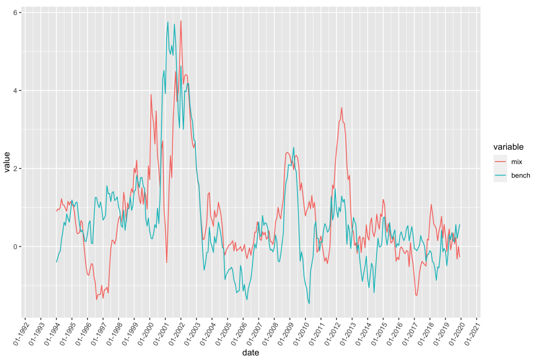
(c) Prof



(d) Valprof



(e) Nissa



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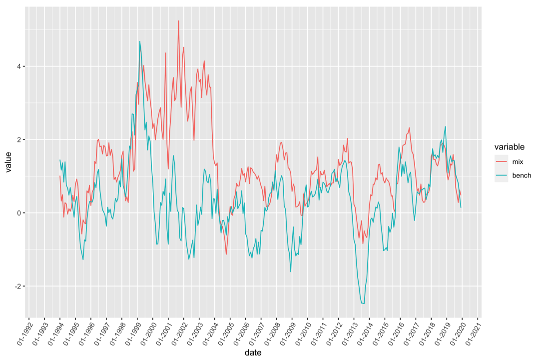
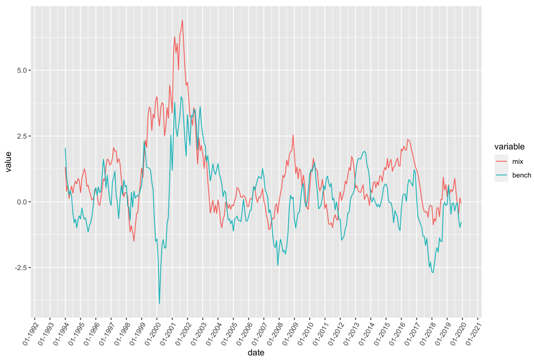
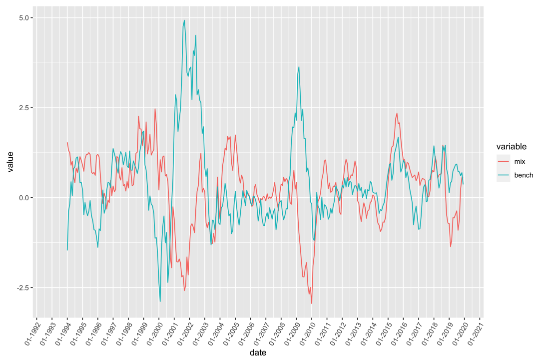


Figure C.3 continued

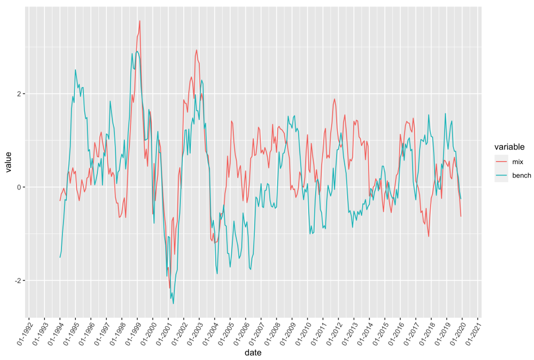
(a) Growth



(b) Aturnover



(c) Gmargins



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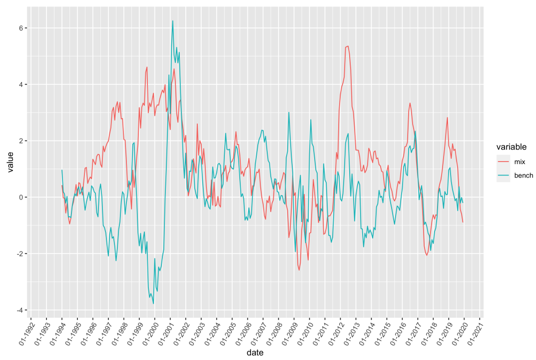

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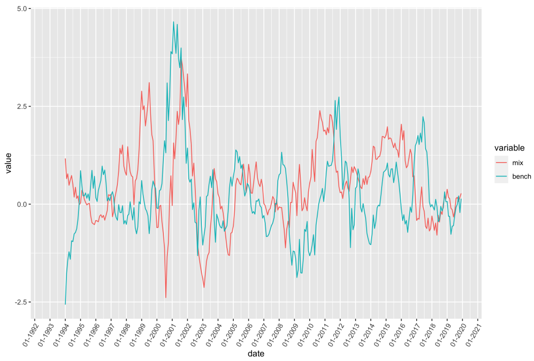

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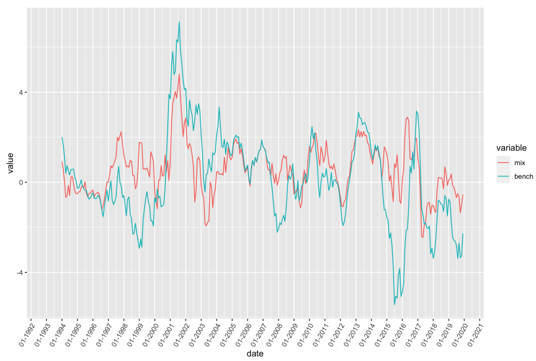

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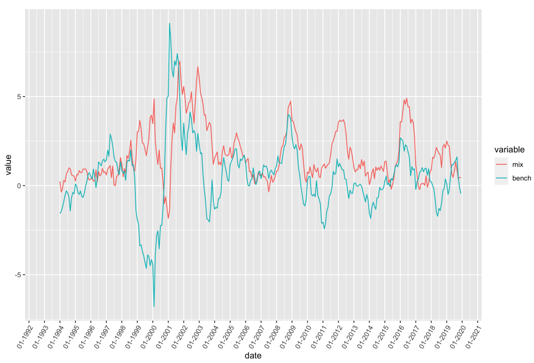

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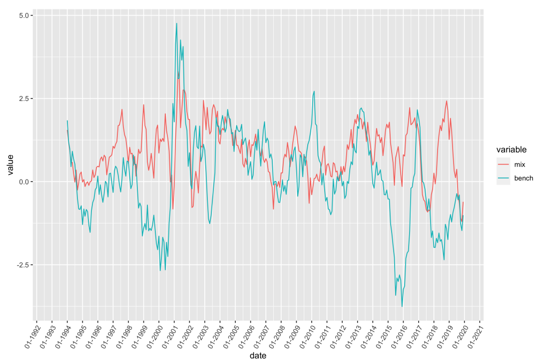
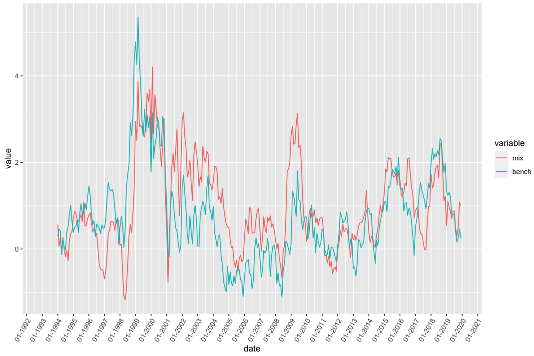


Figure C.3 continued

(a) Noa



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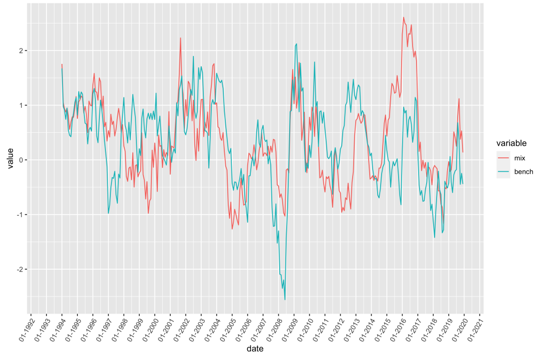

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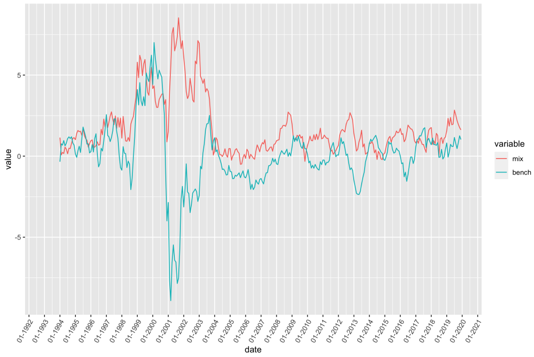
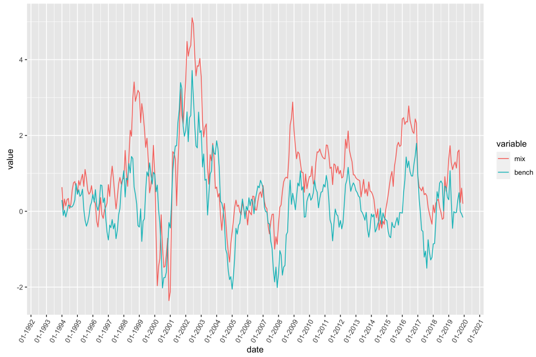


(d) Igrowth



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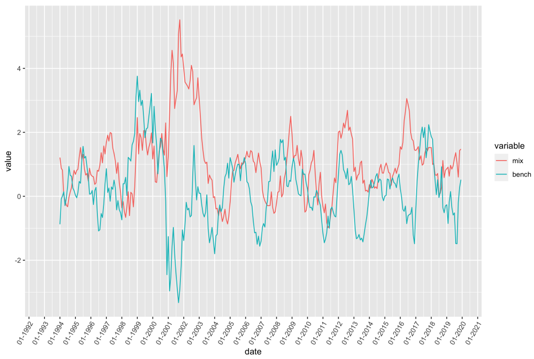

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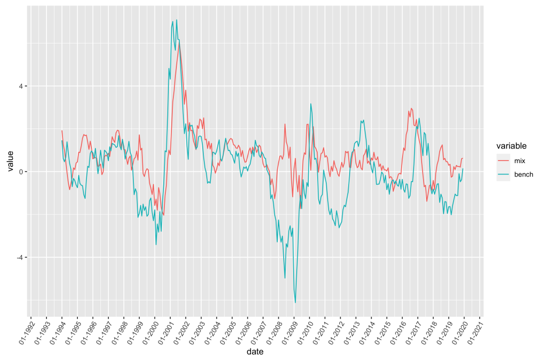

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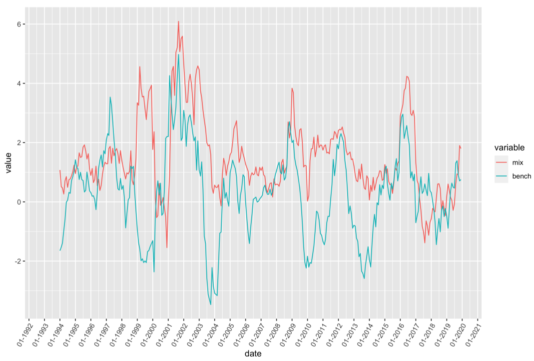

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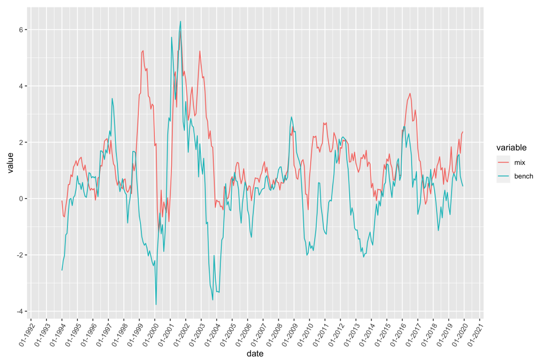
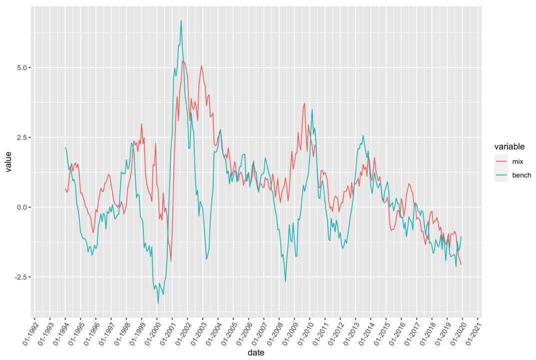


Figure C.3 continued

(a) Sp



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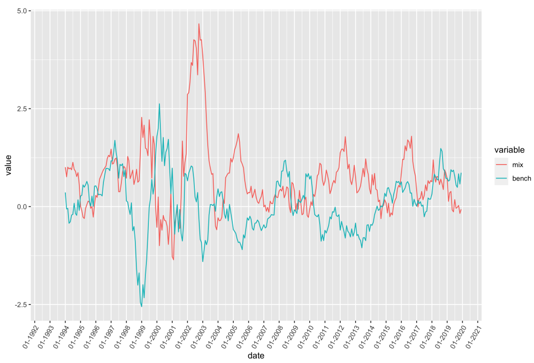
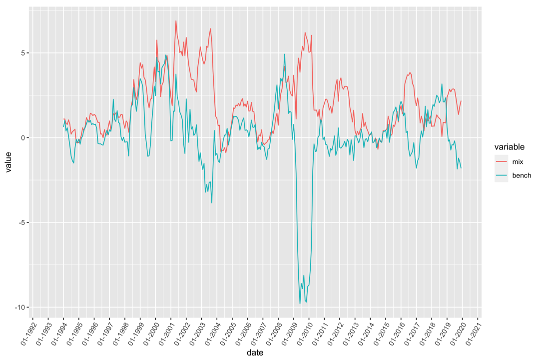


(c) Mom



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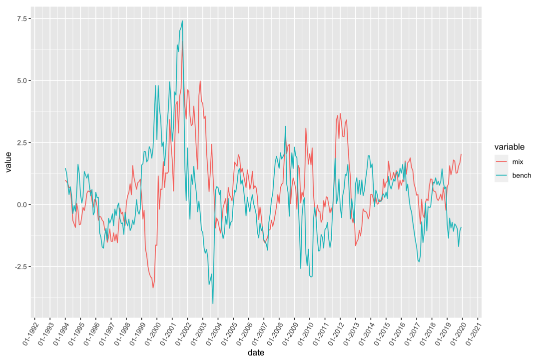

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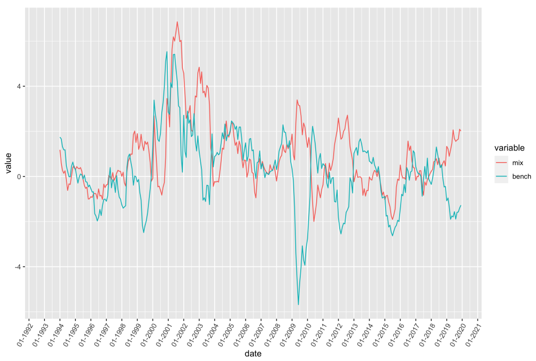

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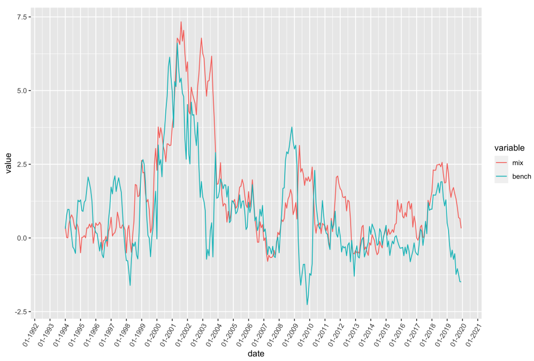

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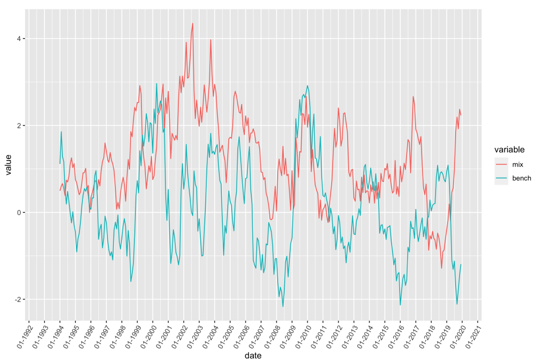


(h) Momrev

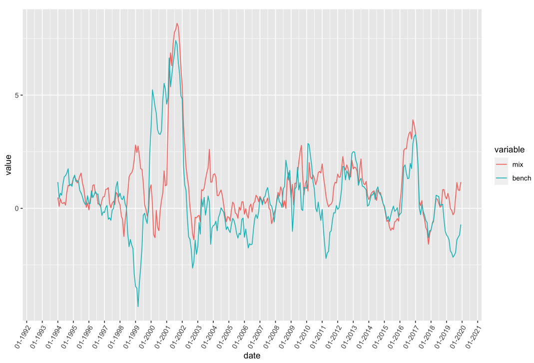
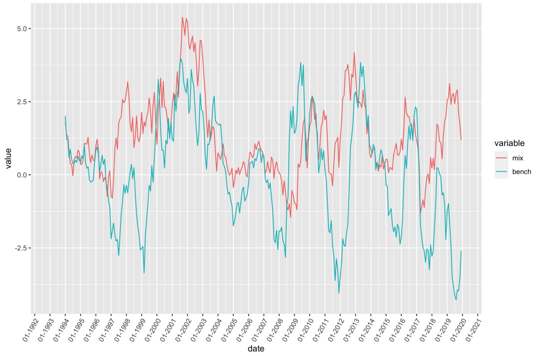


Figure C.3 continued

(a) Lrrev



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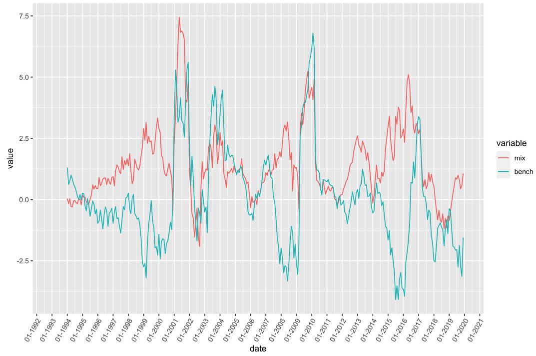

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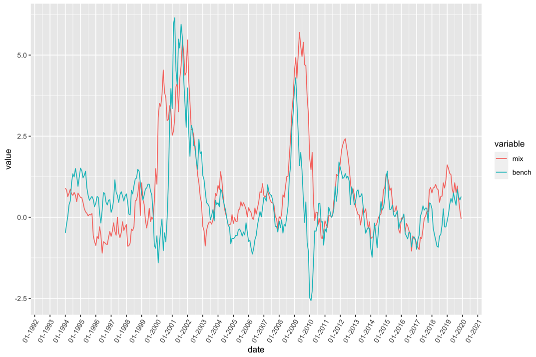

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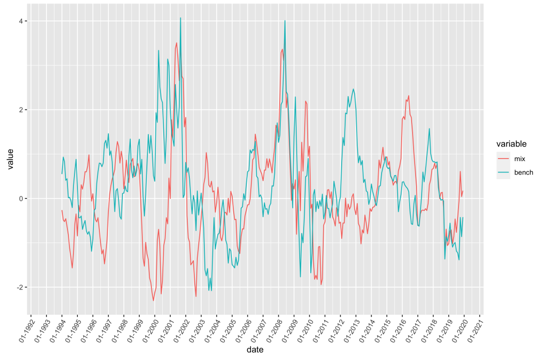

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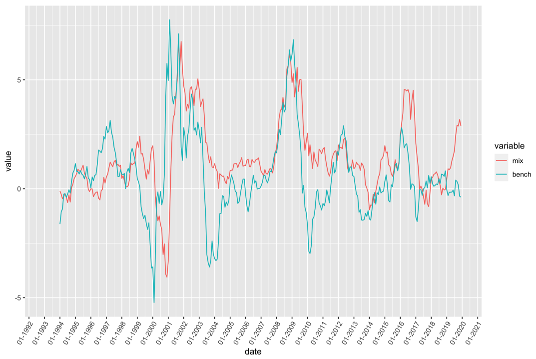

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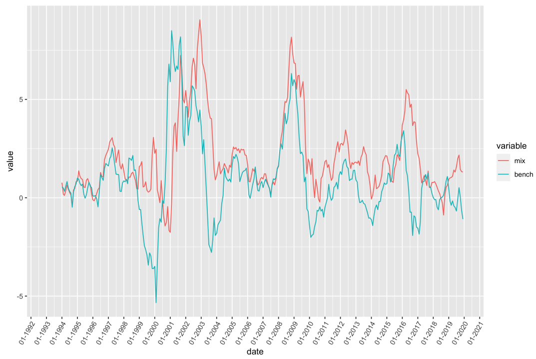

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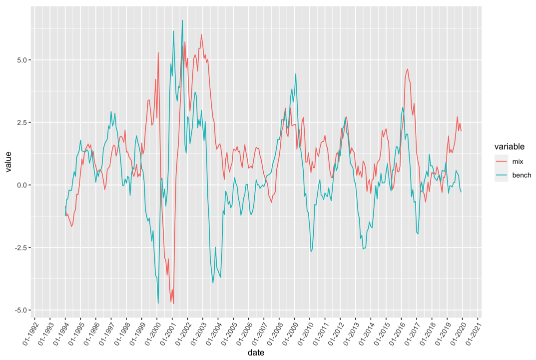

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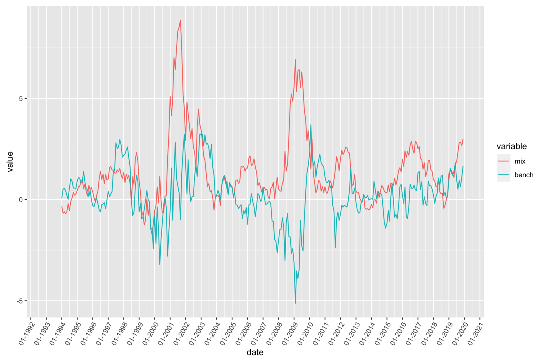

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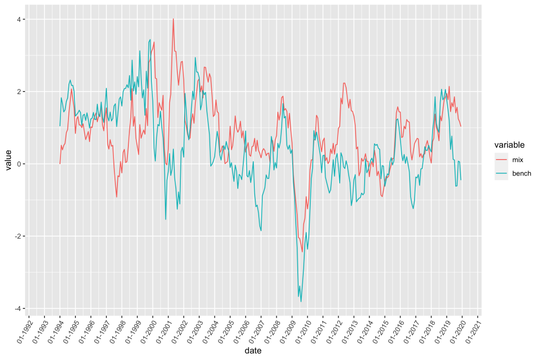
(a) Season



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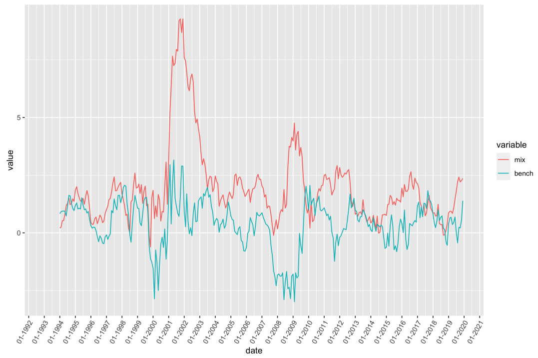

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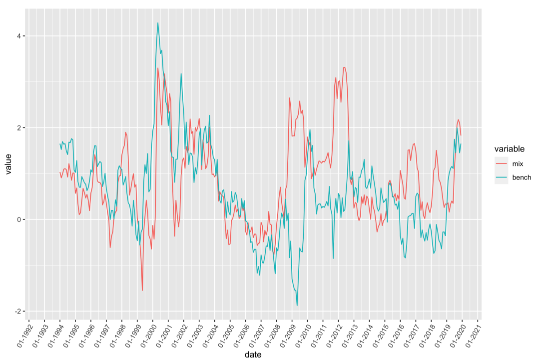

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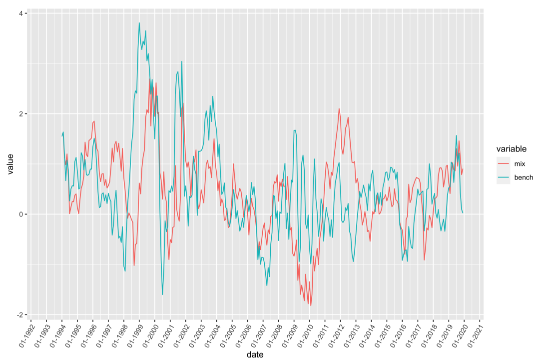

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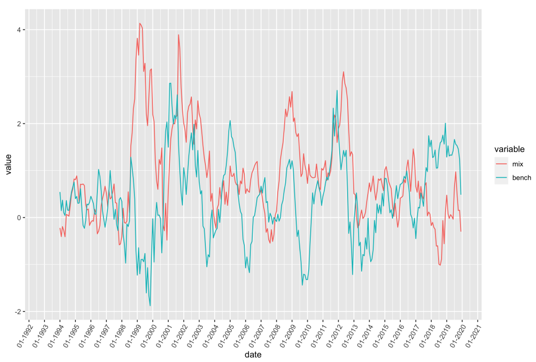

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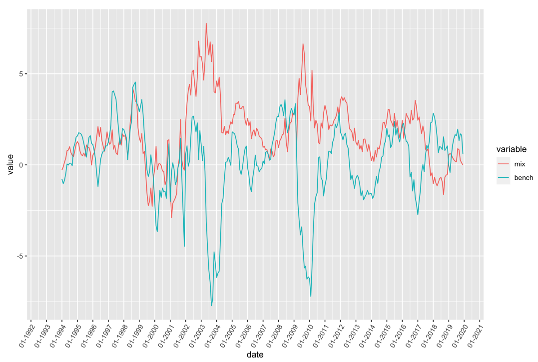
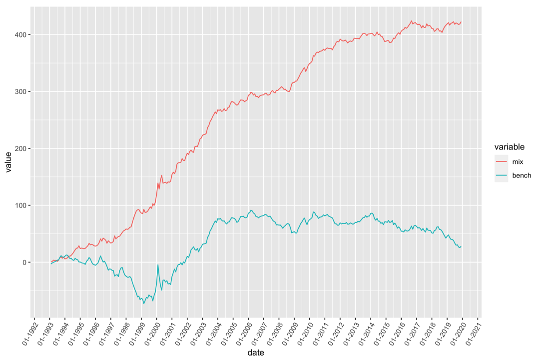


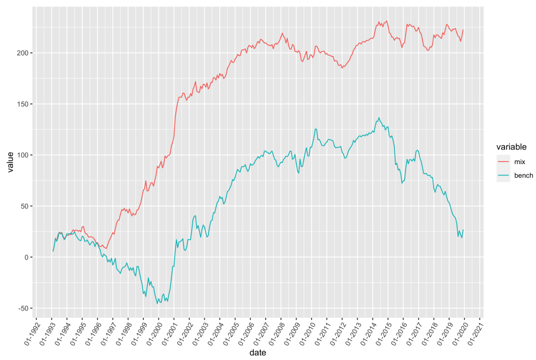
Figure C.9: Cumulative returns of the long minus short returns.

In these figures, we plot the cumulative returns' time series of the deciles-based and benchmark strategies returns. **Deciles-based strategy:** Go long the decile with the highest expected return and go short the decile with the lowest expected return. **Benchmark strategy:** Go long the first (last) decile and go short the last (first) decile based on which extreme decile has the highest average return. See section 3.2.1 in the main text.

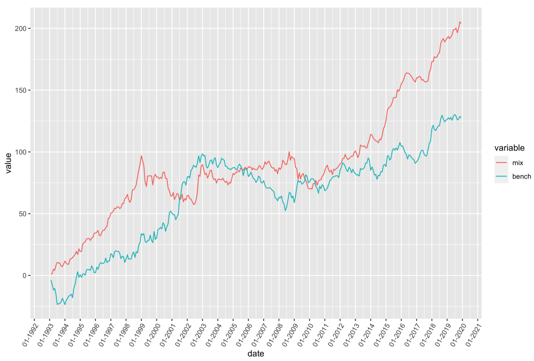
(a) Size



(b) Value



(c) Prof



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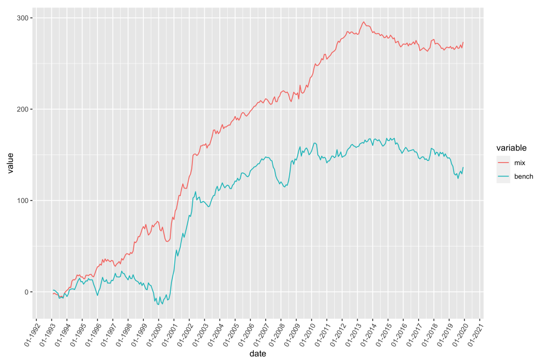
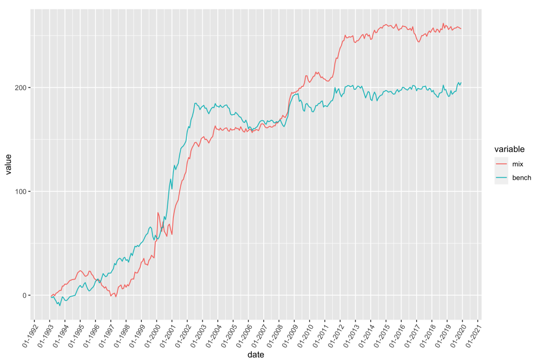


(e) Nissa



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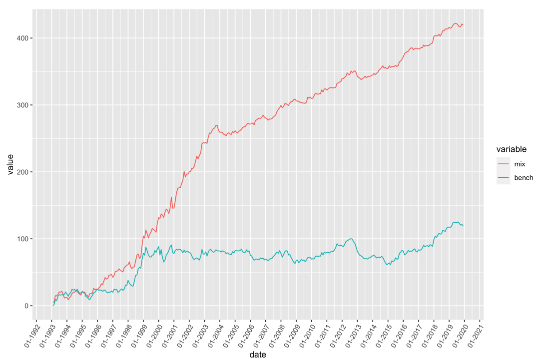
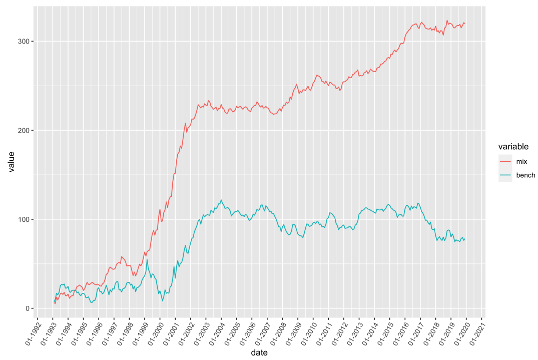
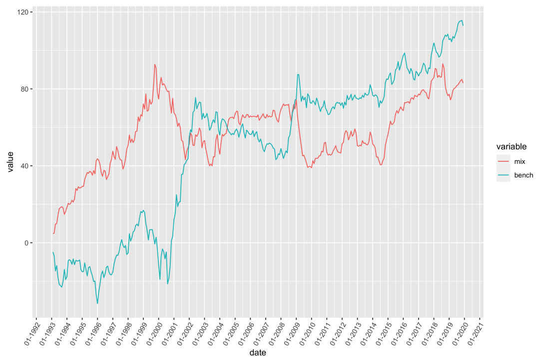


Figure C.9 continued

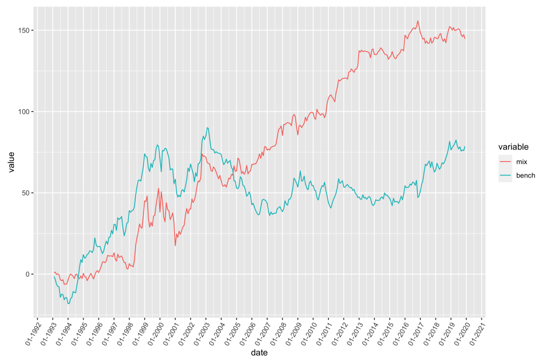
(a) Growth



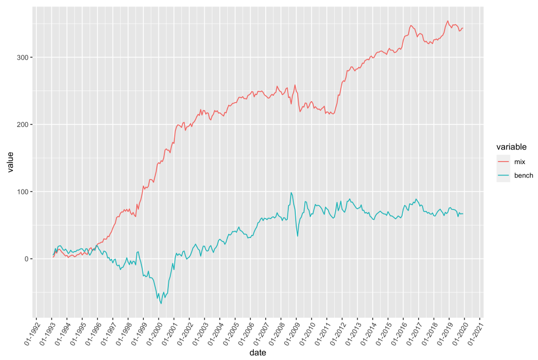
(b) Aturnover



(c) Gmargins



(d) Divp



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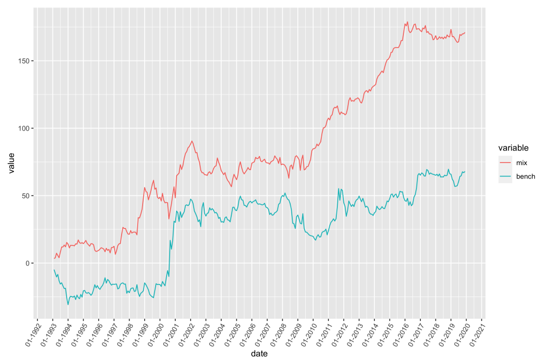

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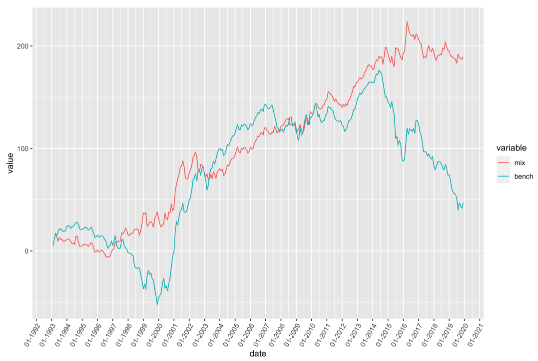

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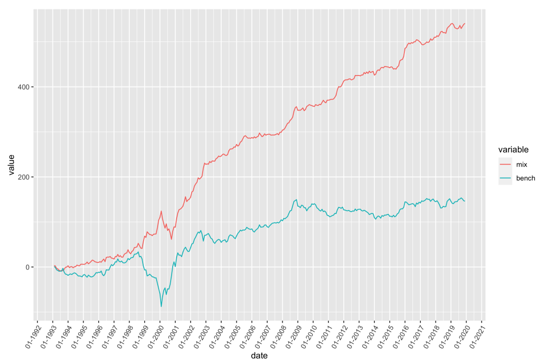

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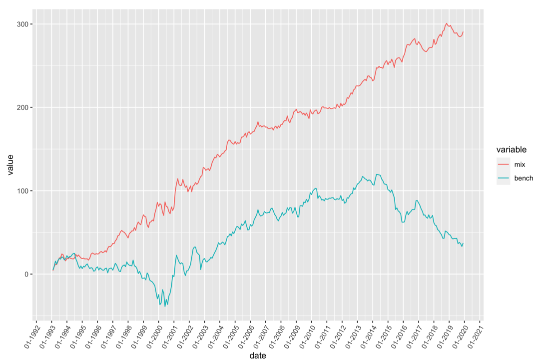
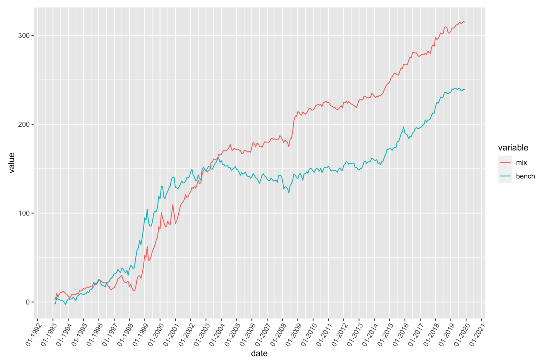
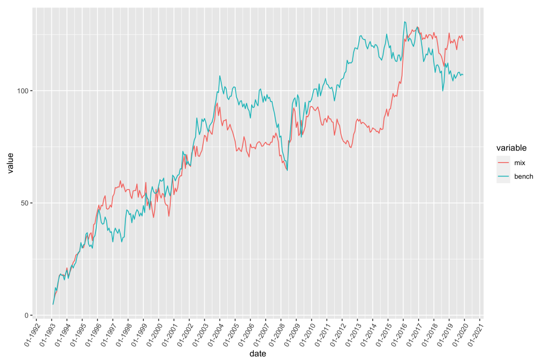


Figure C.9 continued

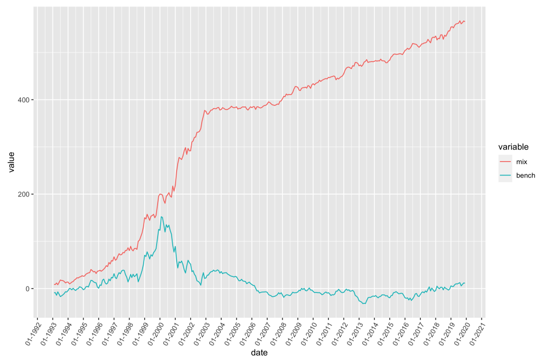
(a) Noa



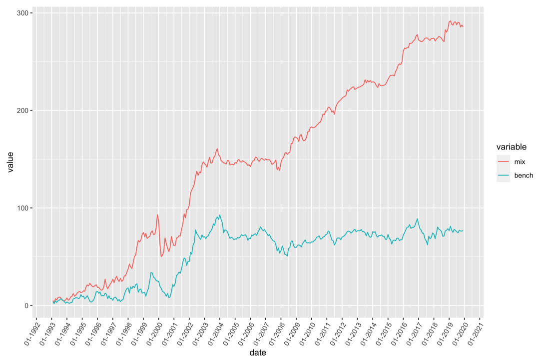
(b) Inv



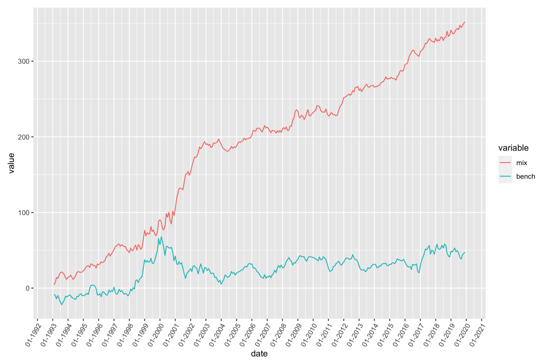
(c) Invcap



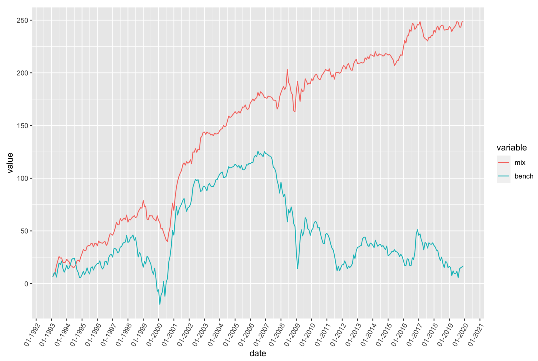
(d) Igrowth



(e) Sgrowth



(f) Lev



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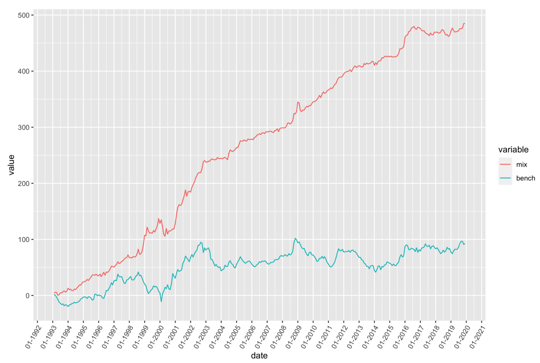

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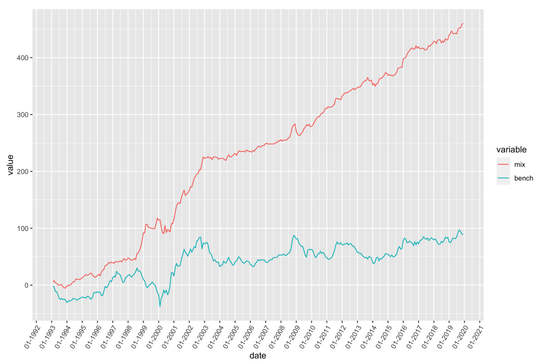
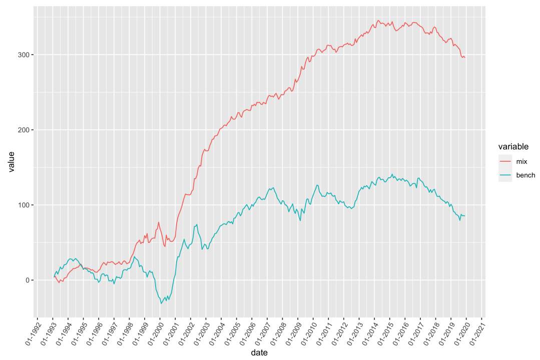


Figure C.9 continued

(a) Sp



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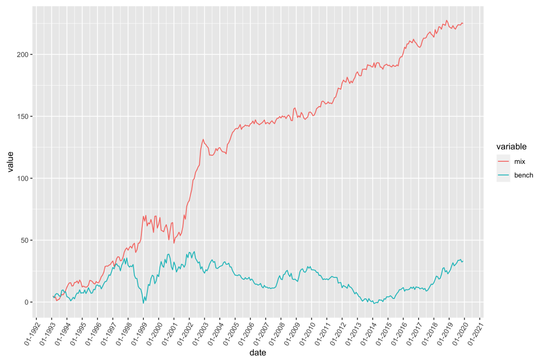
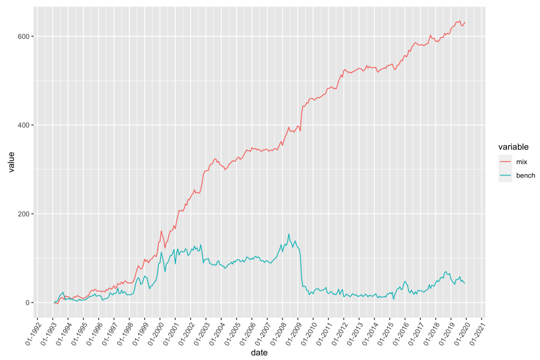


(c) Mom



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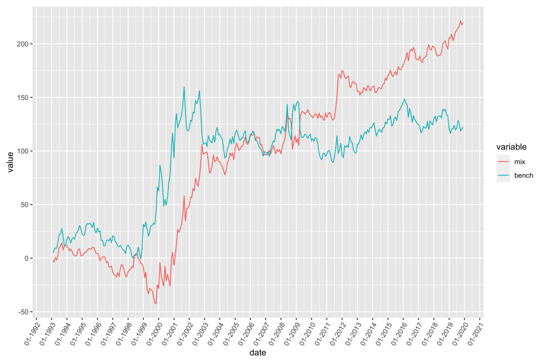

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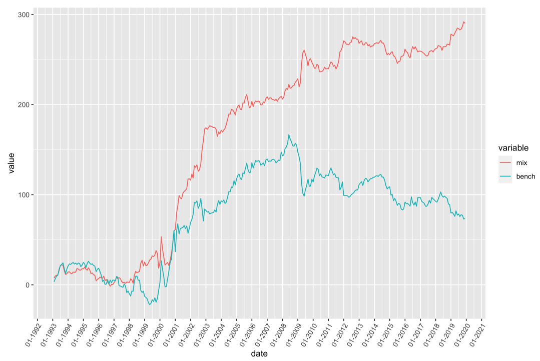
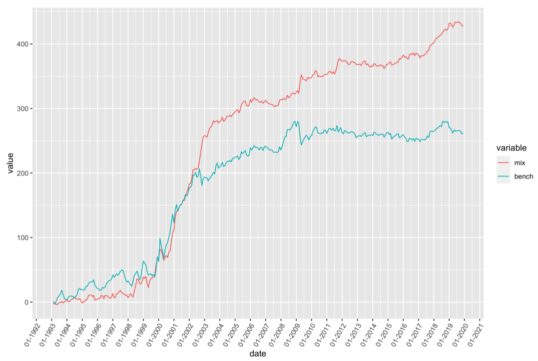


(f) Valmomprof



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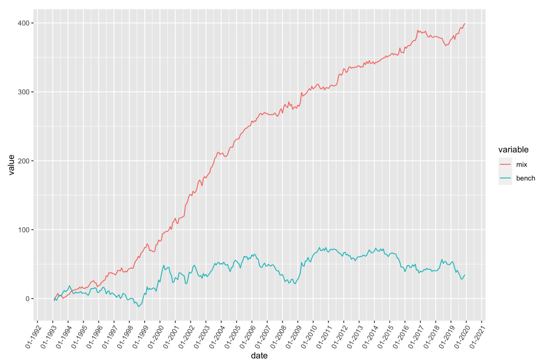

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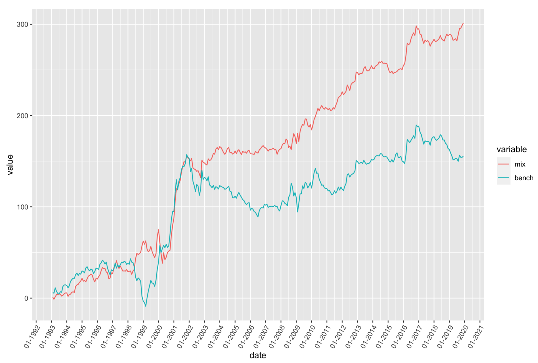
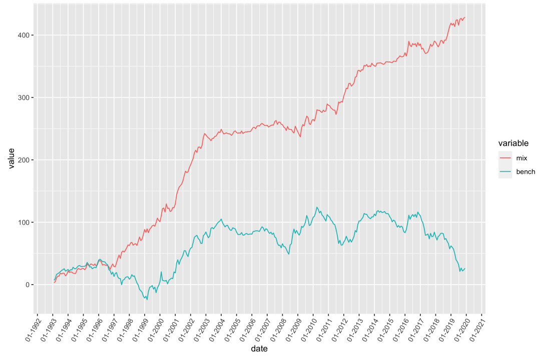


Figure C.9 continued

(a) Lrrev



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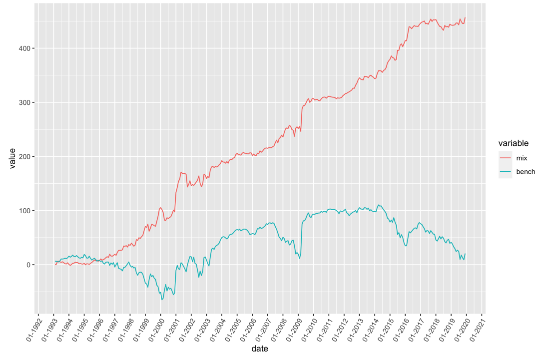

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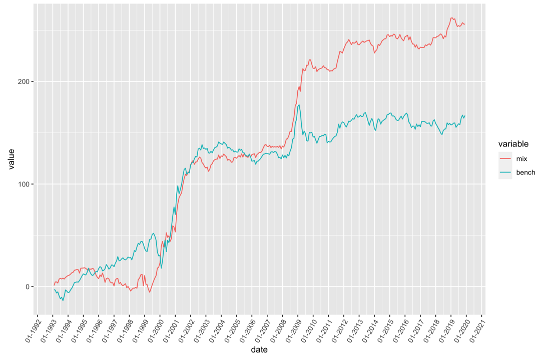

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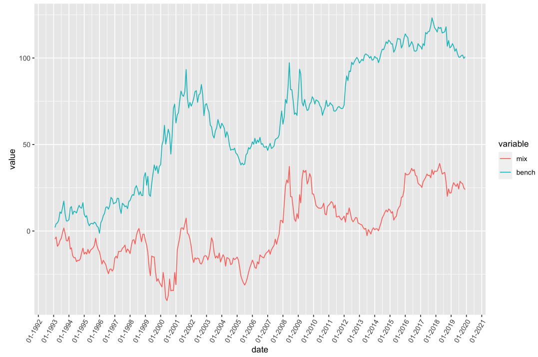

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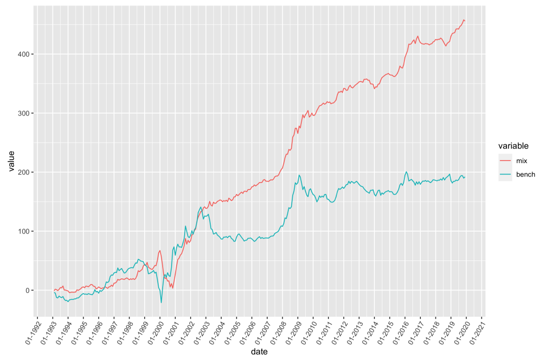
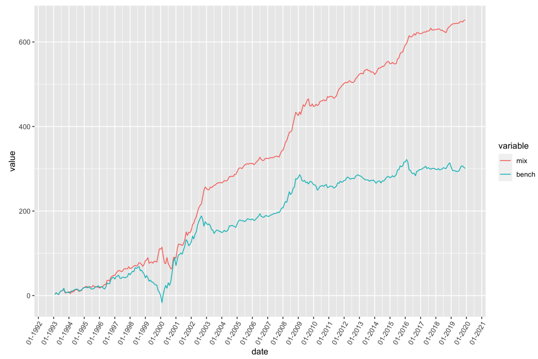


(f) Rome



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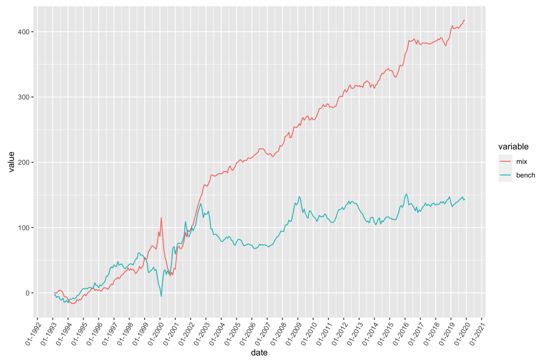

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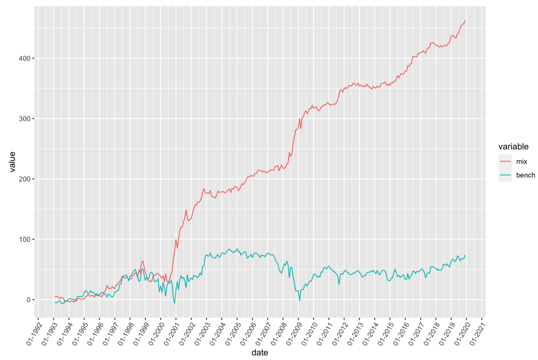
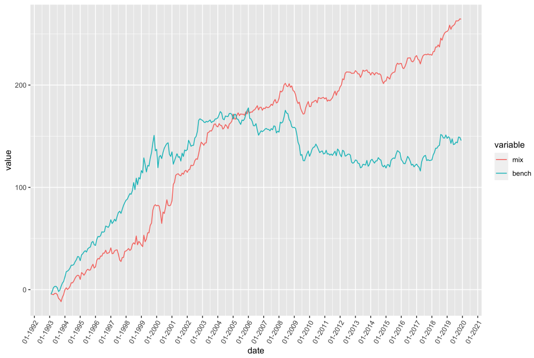


Figure C.9 continued

(a) Season



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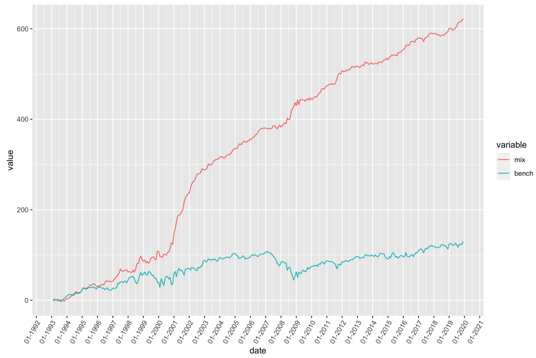

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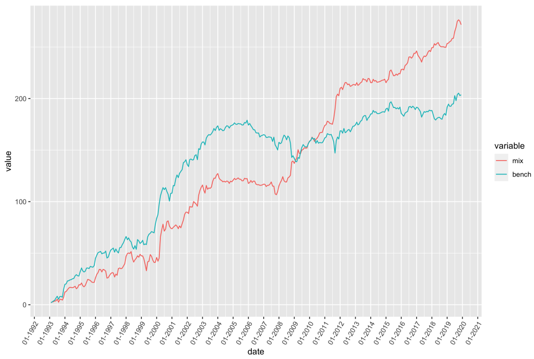

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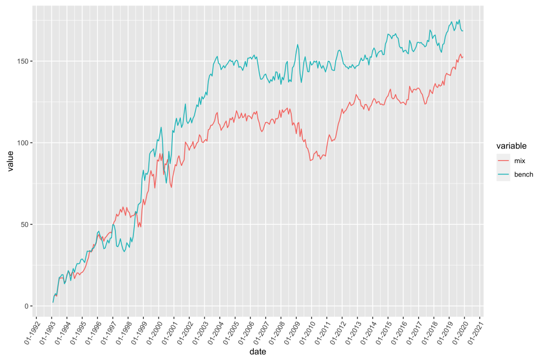
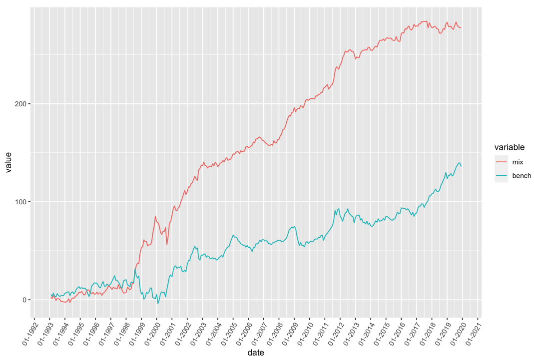


(e) Ciss



(f) Price