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Essays in International Finance and Asset Prices



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A thesis submitted for the degree of
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Declaration

I declare that any material contained in this thesis has not been submitted for a degree to any other university. I further declare that the paper titled “Currency Returns and Interest Rate Surprises: It’s All in the Shocks”, drawn from chapter two of this thesis, is co-authored with Juan Antolin-Diaz, Gino Cenedese and Lucio Sarno. I also declare that the paper titled “Fundamental Momentum: The Impact of Trade Balance News on Currency Trends”, drawn from chapter three of this thesis, is co-authored with Lucio Sarno and Maik Schmeling.

Shangqi Han
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Abstract

This thesis comprises three essays on international finance and asset prices. The research uses international macroeconomic data and asset prices to answer questions in the field of macro-finance. The first chapter shows that global inflation risk is priced in the international equity market and that its risk premium is strongly time-varying. This time variation is intimately tied to the fluctuations in the cyclical nature of inflation around the world. Indeed, I document a simultaneous shift in the global inflation risk premium and the covariance between inflation and future consumption growth during the 2008 financial crisis. I rationalise the time variation and sign-switch in the predictive content of inflation with the effect of the zero lower bound (ZLB).

The second chapter is co-authored with Juan Antolin-Diaz, Gino Cenedese and Lucio Sarno and focuses on the impact of the US monetary policy on currencies. We find that currencies that react more negatively to tightening monetary policy shocks or more positively to positive central bank information shocks earn higher average excess returns. Currency characteristics help explain the heterogeneity of this reactivity across currencies and over time. We build exposure indices to gauge this effect using high-frequency co-movement of interest rates and stock prices around policy announcements. Long-short trading strategies that use such exposure indices as a signal display significant alpha after controlling for the dollar and carry factors. Thus, investors require compensation to hold the currencies that are more sensitive to the US monetary policy.

The third chapter is co-authored with Lucio Sarno and Maik Schmeling. It provides an empirical investigation of the importance of trade balance news in explaining the puzzling high returns to the well-known ‘currency price momentum’ strategy, i.e. the currency strategy that relies on past return continuation among winner and loser currencies. To do this, we introduce another currency strategy, denoted as trade news momentum, which is driven by the heterogeneous currency responses to trade balance news announcements. We find that returns to the trade news momentum command strong explanatory power toward the currency price momentum alpha. Furthermore, we show that the cross-sectional variation in the currency exposure to trade news is understandable in terms of basic economics of exchange rate regimes and the level of capital account restrictions of a country.

Introduction

Understanding the asset market returns through the lens of global economic condition fluctuations is a core issue in asset pricing (Cochrane, 2017). The literature on international macro-finance evolved rapidly as the global financial crisis of 2007-2008 and the COVID-19 pandemic in early 2021 illustrate how important it is to bring asset pricing and portfolio choice considerations into the context of international macroeconomics.

This thesis presents an empirical investigation of the movement in international asset market returns pertaining to global inflation risk, the US monetary policy, and the US trade balance news announcement. The main body of the thesis is developed in the following three chapters, each presenting an essay. The order of the essays is reverse chronological and thus reflects the latest development of the research first. These chapters are followed by concluding remarks of the thesis. This introduction gives a broad context to the thesis by providing a summary of findings for each chapter and outlining their contribution to the existing literature.

Summary of findings

The first chapter analyses the topical issue of global inflation risk in the international equity market. This essay shows that global inflation risk is priced in the international equity returns and that this global inflation risk premium is strongly time-varying and has increased markedly since the 2008 global financial crisis. The fluctuations in the cyclical nature of inflation are the key to understanding the historical changes in the inflation risk premium. Specifically, this essay documents new empirical evidence of a simultaneous global shift in the global inflation risk premium and predictive content of global inflation, changing from counter-cyclical to pro-cyclical. Then, I rationalise this time-variation and sign-switch with various types of macroeconomic shocks in the presence of the zero lower bound (ZLB). Away from the ZLB, when changes in the monetary policy rate broadly neutralise demand fluctuations, supply-shock-lead inflation is counter-cyclical and contains bad news for future consumption. The inflation risk premium is thus negative. However, when the presence

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of the ZLB limits the capacity of the traditional stabilisation policy, inflation can become pro-cyclical and contain good news, leading to the observed increased risk premium.

I define the nominal-real covariance *à la* Boons et al. (2020) as the slope coefficient in a conditional regression of real consumption growth on lagged inflation to assess the predictive content of inflation at any point in time. The literature documents that US inflation predicts real consumption growth in a time-varying way. The inflation-consumption covariance was negative in the 1970s and 1980s; it increased and approached positively in the early 2000s and turned positive during the 2008 financial crisis. Beyond the US, I find international evidence that a global version of the nominal-real covariance is also strongly time-varying. The global nominal-real covariance was negative historically but has been increasing since the 1990s and turned positive during the zero lower bound era from 2009 to 2015.

To understand what is driving the time-variation, I incorporate the models on changes in monetary policy regimes (Campbell et al., 2014; Song, 2017) and the effect of the ZLB (Bilal, 2018) and formally test the role of the expected duration of the ZLB in the determination of inflation cyclical property. The findings align with the mechanism that as the changing expected duration of the zero lower bound varies the feasibility of the traditional stabilisation policy, the cyclical properties of inflation fluctuate correspondingly. In particular, when the policy rate is far above the ZLB, demand shocks are primarily absorbed by the policy rate changes. The dominating supply shocks give rise to the negative covariance between inflation and consumption growth. However, the current short rates, cannot fall (much) when the interest rate is close to or constrained by the ZLB. As a result, demand shocks are magnified, leading to a higher or even positive nominal-real covariance.

Next, the chapter conducts a battery of asset pricing tests in the spirit of Boons et al. (2020). A cross-section of international equity indices reveals that global nominal-real covariance is a statistically significant and economically strong predictor of the inflation risk premium. Specifically, the conditional inflation beta, which is the coefficient in a rolling regression of returns on unexpected inflation, measures how much inflation risk a given country's equity index carries. For a high-minus-low portfolio created by ranking country stock indices according to their inflation beta, an increase in the annualised expected return of 4.8% is predicted by a one standard deviation rise in the nominal-real covariance. This increase suggests that the global inflation risk premium can change signs, given an unconditional average return for the high-minus-low inflation beta portfolio of -5.5%.

It makes intuitive sense that higher inflation predicts poorer future consumption growth when the nominal-real covariance is negative (as it was, for example, in the 1970s). Therefore, countries with high inflation beta are desirable to hedge against bad states and have lower premia. In contrast, a positive shock to inflation carries good news for future consumption

once the nominal-real covariance turned positive (post-2009, for example). The premium for inflation risk is higher in countries with lower inflation betas because they are more attractive to hedge.

To further clarify the aforementioned explanation, I conduct pooled predictive regressions for the returns of five inflation beta-sorted portfolios on their conditional inflation betas, the nominal-real covariance, and an interaction term. In contrast to the other two (non-interaction) components, I find that the interaction term predicts returns well. Therefore, understanding the cross-section of global inflation risk premia involves knowledge of both the nominal-real covariance at each point in time as well as the relative size of inflation betas across countries.

I build on the Boons et al. (2020)’s consumption-based model by including the shadow rate in order to give a theoretical foundation for the previous empirical evidence. To account for sign reversals, I model the exogenous nominal-real covariance process to follow a mean-reverting process with a time-varying intercept given by the shadow rate. The shadow rate is assumed to be an exogenous state variable with a long-run steady state mean and constant volatility that is determined by the stance of monetary policy. I demonstrate analytically that adding the shadow rate preserves the key results in Boons et al. (2020) regarding the implied inflation risk premium while making the sign-switching process of the nominal-real covariance economically meaningful. Then, I summarise and discuss the main model takeaways in Boons et al. (2020) to interpret my empirical finding regarding the global inflation risk premium.

In the model, the nominal-real covariance controls the time-varying predictive content of inflation on future real consumption growth. One of the key takeaways is that both the price of inflation risk and the quantity of inflation risk are linear functions of the nominal-real covariance. Thus the inflation risk premium is quadratic in the nominal-real covariance. These model implications motivate the empirical findings that variation in inflation beta (i.e. the quantity of inflation risk) contains important information about returns when combined with the nominal-real covariance (i.e. the price of inflation risk).

The next two essays, chapters two and three, turn to the increasingly more popular laboratory for the studies of international macro-finance—the foreign exchange (FX) market.

Chapter two is co-authored with Juan Antolin-Diaz, Gino Cenedese and Lucio Sarno and focuses on the impact of the US monetary policy on currencies. In this chapter, we focus on the heterogeneous impact of the US monetary policy on currencies as follows. First, we purge monetary policy shocks from information shocks that may confound the effect on currencies. Second, we regress currency returns on the different structural shocks interacted with time-varying characteristics to obtain an “exposure index” (EXP) for each

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shock for every currency. Finally, we evaluate the economic magnitude of these effects by building long-short portfolios that sort currency on the different EXP indices and analyse their behaviour.

To distil the pure monetary policy effect on currencies, we carefully separate the monetary policy from other contemporaneous effects, particularly central bank information shocks. Jarociński and Karadi (2020) show that central bank announcements simultaneously convey information both about monetary policy and the central bank's assessment of the economic outlook. One can identify a monetary policy shock through a negative co-movement between the rate surprises and stock price changes. By contrast, a positive co-movement must reflect something in the central bank's announcement that is not news about monetary policy—a central bank information shock. The separation of the two components is crucial as a positive information shock leads to an improvement in economic activity, thus offsetting the tightening monetary policy. By analysing the co-movement of interest rates and stock prices in a narrow policy announcement window, we decompose interest rate innovations around the Federal Open Market Committee (FOMC) announcements into monetary policy and central bank information shocks.

Equipped with the two decomposed shocks, we now illustrate their distinct effect on exchange rates using simple univariate regression. We focus on exchange rates against the US dollar for the following 16 countries/regions: Australia, Brazil, Canada, Czech Republic, Euro Area, United Kingdom, Hungary, Japan, Mexico, Norway, New Zealand, Poland, Singapore, South Africa, Sweden, and Switzerland. For each currency, we regress the intraday spot rate return onto the monetary policy rate changes or decomposed shocks, respectively. Thus, the coefficients on the policy-related variables capture the heterogeneous response of each currency.

The results of this simple exercise highlight two takeaways. First, separating the monetary policy from the offsetting information shock is crucial in analysing its effect on currencies. We find that the average response of currencies is negative to surprising US rate increases and tightening monetary policy shocks. This observation that foreign currencies tend to depreciate with contractionary policy is in line with the vast literature on the effect of monetary policy on exchange rate (e.g. Dornbusch, 1976; Kim et al., 2017; Rogers et al., 2018). In contrast to the policy shocks, there are heterogeneous responses among currencies to a positive information shock. The positive information shock about the macroeconomic outlook may command an offsetting effect on the accompanying rise in interest rate. Thus, we observe that foreign currencies can appreciate or depreciate with information shocks depending on which effect dominates. Overall, currencies tend to depreciate on tightening policy shocks but tend to appreciate when there are contemporaneous positive information shocks.

The second takeaway is that fundamental variables like interest rate differentials help explain currencies' heterogeneous responses. To see this, we summarise country-specific average responses along currencies' interest rate differentials. Despite the large difference in their interest rate level, the Japanese yen and Brazilian real react similarly to a 1% change in the US policy rate, where they both depreciate around 4%. This finding is unsurprising as the policy rate innovations do not disentangle the monetary policy shocks from the information shocks. The impact of monetary policy on currencies is thus underestimated because the positive information shocks have offsetting effects. In fact, a 1% tightening shock in the US monetary policy is associated with a large 8.2% depreciation in the Brazilian real. In contrast, the same movement in the central bank information shock is associated with around 4.6% appreciation in the Brazilian real. On the contrary, low interest rate currencies like the Japanese yen react at a smaller magnitude to policy and information shocks (-4.4% and -3.1%).

Motivated by the two above-mentioned stylised facts, this chapter presents how to construct an “exposure index” that captures the cross-sectional and time-series differences in sensitivity to the different structural shocks among currencies. Specifically, our regressions use the cross-product of the policy-related variables with currency characteristics linked to policy sensitivity. This approach to incorporating time variation exposure follows the seminal work by Shanken (1990); and builds on the methods of Pástor and Stambaugh (2003) and Ozdagli and Velikov (2020). The characteristics underlying the EXP index capture the effects of various monetary policy transmission mechanisms, including interest rate differentials, trend CPI inflation differentials, the ratio of net foreign assets (NFA) over GDP, the beta of the currency to the US equity market, and a measure of “trade network centrality” that measures countries' exposure to global shocks. We show that currencies tend to be more reactive to the US monetary policy if they are associated with net borrowers countries, peripheral in the global trade network, characterised by higher interest rates, and more exposed to equity risk.

Finally, we evaluate the economic magnitude of the monetary policy effects by building long-short portfolios that sort currency by the EXP indices and analyse their behaviour. We find that our EXP index is a strong predictor of returns in the cross-section of currencies. Specifically, currencies that are more sensitive to the US monetary policy (i.e. those that perform poorly when there is a tightening policy shock and those that perform well when there is a positive information shock) have significantly higher average returns than less sensitive currencies. A long-short trading strategy designed to exploit this effect achieves an annualised return of 5.18% with an annualised Sharpe ratio of 0.69 in an out-of-sample exercise from 2009 to 2019. While some of this return is captured by existing factor models, the strategy earns an annualised abnormal return of 3.47% even after controlling for the

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dollar and carry factors. Overall, the performance of the exposure strategy indicates that the effect of monetary policy is economically important even in the low interest rate environment post-2009. Thus, investors require compensation to hold the currencies that are more sensitive to the US monetary policy.

Chapter three is co-authored with Lucio Sarno and Maik Schmeling and turns to understanding currency momentum by studying how different currencies are related to fundamental information in the form of trade balance news. Recent events in the FX market remind us of the potential importance of US trade announcements on exchange rates. Following the US Department of Commerce's release of the US trade report on 10 August 2006, the dollar rallied strongly against currencies including the Japanese yen, euro, British pound, Swiss franc and Canadian dollar. The *Financial Times* on the same day attributed this significant climb of the US dollar to "a mass squaring of short positions betting on a fall on the dollar" after the no-worse-than-expected trade data reassure the traders (Johnson, 2006). Therefore it naturally calls for the identification and documentation of the important role of trade balance news releases. Specifically, our motivation for focusing on trade figure announcement is twofold: (i) balance of trade is a crucial component of a nation's current account, and it is comparable to the cashflow proxies (e.g. earnings) for a company, and (ii) announcements bring resolution to trade imbalance uncertainty and thus move currency excess returns (Della Corte et al., 2016; Mueller et al., 2017).

Our empirical analysis shows that the overall currency market movement is larger on trade news announcements days than on non-announcement days. Indeed, the trade news announcement occurrence is a significant positive predictor of the time variation in the absolute dollar factor. To further measure the market participants' reaction at the currency level, we compute the cumulative three-day abnormal returns for each currency around every trade news announcement in the spirit of Novy-Marx (2015). In turn, we form the macro fundamental currency momentum - trade news momentum - by longing the currencies that receive positive market reactions and shorting the currencies that receive negative market reactions.

We find a large Sharpe ratio to the trade news momentum of 0.54 per annum (p.a.). Importantly, trade news momentum is related to but different from the past price momentum documented in Menkhoff et al. (2012b) in terms of the spreads in their corresponding trading signal, portfolio return characteristics, return correlations and portfolio compositions. Trade news momentum is also different from the widespread carry trade in FX markets, providing appealing returns that are largely unrelated to carry trade returns.

We continue our investigation of the trade news momentum by taking a time-series perspective. The time-series regressions suggest that the trade news momentum returns are

positively but imperfectly correlated with the returns to the past price momentum. Furthermore, the alpha to the trade news momentum remains positive and significant after controlling for the dollar factor, carry trade and price momentum strategies. Interestingly, the trade news momentum commands strong explanatory power toward the past price momentum alpha. Further analysis of the cross-section of sorted portfolios indicates that investors expect high (low) returns on the past winner (loser) currencies in the price momentum because those currencies receive positive (adverse) market reactions following the trade news releases. This finding suggests that the cross-section predictability of currency's past performance can be rationalised by the corresponding movements in fundamentals, captured by the cross-currency spread in market reactions to the trade news announcement.

To reconcile the novel finding, we investigate what drives the heterogeneity in currencies' exposure to trade news in connection with central bank interventions. We study whether the impact of trade news in cross-section excess return can be attributed to the costs to central banks undertaking more frequent interventions. The hypothesis is that movement in economic fundamentals (e.g. trade balance) will lead to a more potent trending mechanism in returns for currencies whose central banks choose to intervene heavily. The trend-follower should earn more profits from trade news momentum strategies constructed from currencies under heavy interventions.

Subsample analysis confirms the above predictions. We study two dimensions of central bank intervention: capital account controls and exchange rate regime choices. We show that subsamples of currencies with either heavy capital account controls or fixed exchange rates generate stronger trade news momentum than currencies under fewer interventions. These findings support the argument that currencies under interventions can afford less trade imbalance, and their excess return movement is more predictable. Thus, the profitability of trade news momentum can be reconciled with the costs to central banks.

Contribution of the thesis

This thesis contributes to several related strands of literature at the intersection of international macro-finance and empirical asset pricing. This section provides here only a high-level summary.

The first chapter on global inflation risk is related to the substantial interest in the time-varying nature, including sign-switches, of the nominal-real covariance. The interest is motivated by the attempts to reconcile the puzzling sign-switch in the stock-bond correlation with exogenous changes in the cyclical properties of inflation (e.g. Campbell et al., 2014; Campbell et al., 2017; Song, 2017). Further building on the studies on the effects of the zero-

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lower-bound, the first chapter is complementary to this literature by providing theoretical discussion and empirical evidence on the implication of the low interest rate environment on the determination of inflation cyclical property. The first chapter also contributes to the empirical literature on inflation by presenting new evidence concerning global inflation risk premia. The majority of works on estimating the inflation risk premium in the cross-section of stocks focused on the unconditional asset pricing implication (e.g. Chen et al., 1986; Ferson and Harvey, 1991; Bekaert and Wang, 2010; Ang et al., 2012). Extending and building on the US study by Boons et al. (2020), this chapter contributes to this literature by providing international evidence for the shift in the time-varying global inflation risk premium and the corresponding change in the global nominal-real covariance.

Chapter two studies the impact of the US monetary policy on currencies and relates to the extensive literature on the effects of monetary policy on exchange rates (e.g. Dornbusch, 1976; Eichenbaum and Evans, 1995; Scholl and Uhlig, 2008; Rogers et al., 2014; Kim et al., 2017; Rogers et al., 2018). By taking a cross-section perspective, this chapter contributes to this literature by not only examining the effect of monetary policy on the aggregate dollar exchange rate but also the heterogeneous responses of individual country pairs. This chapter is also related to the literature that assesses the impact of high-frequency financial-market surprises around key monetary policy announcements on asset prices (e.g. Kuttner, 2001; Bernanke and Kuttner, 2005; Gürkaynak et al., 2005). In related work, Jarociński and Karadi (2020) illustrate that policy announcements come with central bank communication about the economic outlook, whose presence can bias the estimated effects of monetary policy. The contribution is thus to investigate the purged monetary policy effect on currencies. The third strand of related literature attempts to use indices based on time-varying firm characteristics to study the cross-section of stock returns (e.g. Shanken, 1990; Pástor and Stambaugh, 2003; Ozdagli and Velikov, 2020). In the context of the currency market, chapter two builds on these papers to study the monetary policy risk compensation in the cross-section of currency returns by relying on currency fundamentals linked to the monetary policy transmission channels of exchange rates.

The importance of trade balance news studied in chapter three relates to the literature documenting that cross-sectional predictability in currencies can be exploited using various investment strategies, especially momentum (Menkhoff et al., 2012b; Asness et al., 2013). Another related strand of the literature attempts to uncover links between momentum and fundamentals (e.g. Novy-Marx, 2015; Dahlquist and Hasseltoft, 2020). The contribution of chapter three to these two strands of literature is to understand currency momentum by studying how different currencies are related to fundamental information in the form of trade balance news. On rationalisation of the excess returns of trade news momentum, chapter

three is also related to the literature on central bank intervention practices (e.g. Fratzscher et al., 2019).

Chapter 1

Time-Varying Global Inflation Risk and the Zero Lower Bound

1.1 Introduction

“The 10-year break-even rate, a market-based gauge of investors’ inflation forecasts over the next 10 years, has held in a roughly 2.75 to 3 per cent range in recent weeks, far lower than the March 2022 inflation rate of 8.5 per cent.”

– Platt and Smith (2022), *Financial Times*

Break-even inflation rates, also known as “inflation compensation”, are widely used by market commentators to gauge investors’ inflation expectations. A straight read of the apparent divergence between the break-even rate and the inflation rate might suggest that the market is expecting inflation to come down despite the soaring cost of living. However, Gürkaynak et al. (2010) argue that, in addition to inflation expectations, the inflation risk premium is another crucial element of inflation compensation. Thus, identifying the magnitude and sign of the inflation risk premium helps in understanding the inflation compensation that is embedded in the international asset market.

This paper shows that global inflation risk is priced in the international equity returns and that this global inflation risk premium is strongly time-varying and has increased markedly since the 2008 global financial crisis. The fluctuations in the cyclical nature of inflation are the key to understanding the historical changes in the inflation risk premium. Specifically, this paper documents new empirical evidence of a simultaneous global shift in the global inflation risk premium and predictive content of global inflation, changing from counter-cyclical to pro-cyclical. Then, I rationalise this time-variation and sign-switch with various types of macroeconomic shocks in the presence of the zero lower bound (ZLB). Away from

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the ZLB, when changes in the monetary policy rate broadly neutralise demand fluctuations, supply-shock-lead inflation is counter-cyclical and contains bad news for future consumption. The inflation risk premium is thus negative. However, when the presence of the ZLB limits the capacity of the traditional stabilisation policy, inflation can become pro-cyclical and contain good news, leading to the observed increased risk premium.

I define the nominal-real covariance *à la* Boons et al. (2020) as the slope coefficient in a conditional regression of real consumption growth on lagged inflation to assess the predictive content of inflation at any point in time. The literature documents that US inflation predicts real consumption growth in a time-varying way. The inflation-consumption covariance was negative in the 1970s and 1980s; it increased and approached positively in the early 2000s and turned positive during the 2008 financial crisis. Beyond the US, I find international evidence that a global version of the nominal-real covariance is also strongly time-varying. The global nominal-real covariance was negative historically but has been increasing since the 1990s and turned positive during the zero lower bound era from 2009 to 2015.

To understand what is driving the time-variation, I incorporate the models on changes in monetary policy regimes (Campbell et al., 2014; Song, 2017) and the effect of the ZLB (Bilal, 2018) and formally test the role of the expected duration of the ZLB in the determination of inflation cyclical property. The findings align with the mechanism that as the changing expected duration of the zero lower bound varies the feasibility of the traditional stabilisation policy, the cyclical properties of inflation fluctuate correspondingly. In particular, when the policy rate is far above the ZLB, demand shocks are primarily absorbed by the policy rate changes. The dominating supply shocks give rise to the negative covariance between inflation and consumption growth. However, the current short rates, cannot fall (much) when the interest rate is close to or constrained by the ZLB. As a result, demand shocks are magnified, leading to a higher or even positive nominal-real covariance.

Next, this paper conducts a battery of asset pricing tests in the spirit of Boons et al. (2020). A cross-section of international equity indices reveals that global nominal-real covariance is a statistically significant and economically strong predictor of the inflation risk premium. Specifically, the conditional inflation beta, which is the coefficient in a rolling regression of returns on unexpected inflation, measures how much inflation risk a given country's equity index carries. For a high-minus-low portfolio created by ranking country stock indices according to their inflation beta, an increase in the annualised expected return of 4.8% is predicted by a one standard deviation rise in the nominal-real covariance. This increase suggests that the global inflation risk premium can change signs, given an unconditional average return for the high-minus-low inflation beta portfolio of -5.5%.

It makes intuitive sense that higher inflation predicts poorer future consumption growth when the nominal-real covariance is negative (as it was, for example, in the 1970s). Therefore, countries with high inflation beta are desirable to hedge against bad states and have lower premia. In contrast, a positive shock to inflation carries good news for future consumption once the nominal-real covariance turned positive (post-2009, for example). The premium for inflation risk is higher in countries with lower inflation betas because they are more attractive to hedge.

To further clarify the aforementioned explanation, I conduct pooled predictive regressions for the returns of five inflation beta-sorted portfolios on their conditional inflation betas, the nominal-real covariance, and an interaction term. In contrast to the other two (non-interaction) components, I find that the interaction term predicts returns well. Therefore, understanding the cross-section of global inflation risk premia involves knowledge of both the nominal-real covariance at each point in time as well as the relative size of inflation betas across countries.

I build on the Boons et al. (2020)'s consumption-based model by including the shadow rate in order to give a theoretical foundation for the previous empirical evidence. To account for sign reversals, I model the exogenous nominal-real covariance process to follow a mean-reverting process with a time-varying intercept given by the shadow rate. The shadow rate is assumed to be an exogenous state variable with a long-run steady state mean and constant volatility that is determined by the stance of monetary policy. I demonstrate analytically that adding the shadow rate preserves the key results in Boons et al. (2020) regarding the implied inflation risk premium while making the sign-switching process of the nominal-real covariance economically meaningful. Then, I summarise and discuss the main model takeaways in Boons et al. (2020) to interpret my empirical finding regarding the global inflation risk premium.

In the model, the nominal-real covariance controls the time-varying predictive content of inflation on future real consumption growth. One of the key takeaways is that both the price of inflation risk and the quantity of inflation risk are linear functions of the nominal-real covariance. Thus the inflation risk premium is quadratic in the nominal-real covariance. These model implications motivate the empirical findings that variation in inflation beta (i.e. the quantity of inflation risk) contains important information about returns when combined with the nominal-real covariance (i.e. the price of inflation risk).

Related literature The work is related to the substantial interest in the time-varying nature, including sign-switches, of the nominal-real covariance. Historically, high inflation is associated with low stock returns, as documented in the early seminal work of Fama and

Schwert (1977). However, this association, together with the stock-bond correlation, changed at the turn of the century. In Campbell et al. (2017), the authors highlight a simultaneous change in the sign of the term premium for US Treasuries and the nominal-real covariance in the early 2000s. Several other papers (e.g. Baele et al., 2010; David and Veronesi, 2013) also documented the puzzling phenomenon that the stock-bond correlation changed from being positive in the 1980s to negative during the recent downturns. There is consensus in this body of literature that fluctuations in the stock-bond correlation can be explained by models that take exogenous changes in the cyclical features of inflation into account. Regarding what is driving the variations in the cyclical properties of inflation, Campbell et al. (2014) and Song (2017) highlight the effect of changes in monetary policy, and Bilal (2018) further theoretically illustrate the impact of the presence of the ZLB. This paper is thus complementary to this literature by providing theoretical analysis and empirical evidence on the implications of the ZLB on the determination of inflation cyclical property.

I also add to the body of empirical literature on inflation by presenting new evidence on inflation risk premia in the global equities market.¹ Early works on inflation risk premium in the cross-section of stocks traced back to the literature on economic risks premium (e.g. Chen et al., 1986; Ferson and Harvey, 1991). Focusing on inflation, Ang et al. (2012) estimate the inflation risk premium in the cross-section of US single stocks. In the international asset market, Bekaert and Wang (2010) estimate the inflation betas for standard bond and country equity indices and argue that such standard securities are poor inflation hedges because their static betas are smaller than one. However, these papers focus on inflation risk's unconditional asset pricing implications. The typical point is a negative inflation risk premium that varies considerably between different sample periods and is not statistically significant. Boons et al. (2020) explain this evidence by documenting a time-varying inflation risk premium that can change sign using the cross-section of US stocks. This paper contributes to this literature by providing international evidence for the change in the global nominal-real covariance and the corresponding shift in the global inflation risk premium.

1.2 Data

US Data I use monthly inflation (Π_t) calculated as the simple rate of change in the seasonally adjusted Consumer Price Index for All Urban Consumers (CPI) available from the U.S. Bureau of Labor Statistics. Monthly per capita real consumption growth (ΔC_t)

¹The emergence of inflation-linked bonds and various term structure models give rise to a vast literature on the estimates of the inflation risk premium in the bond market (e.g. Ang et al., 2008; Bekaert and Wang, 2010; Gürkaynak et al., 2010).

is calculated using seasonally adjusted aggregated nominal consumption expenditures on nondurables and services (from National Income and Product Accounts (NIPA) Table 2.8.5) combined with population numbers (from NIPA Table 2.6) and price deflator series (from NIPA Table 2.8.4). In the exercise involving zero lower bound (ZLB), I use the Federal Funds Effective Rate (FFR) from FRED, Federal Reserve Bank of St. Louis. I consider three measures of the US Shadow Short Rate (SSR), including the LJK Shadow Short Rate by Krippner (2013), the Wu-Xia Shadow Federal Funds Rate by Wu and Xia (2016) and the Structural Shadow Federal Funds Rate by Jones et al. (2021). The US one-month T-bill return and benchmark asset pricing factors are from Kenneth French's website for the asset pricing tests.

International Data For G7 and OECD aggregate², I use quarterly inflation (Π_t) calculated as the simple rate of change in the Consumer Price Index for All Items (from the OECD website). I adjust for seasonality *à la* Harvey (2006a) and Harvey (2006b) in “pseudo real-time” with expanding window.³ Quarterly per capita real consumption growth (ΔC_t) is calculated using seasonally adjusted volume estimates of private final consumption expenditure (from OECD Quarterly National Accounts (QNA) dataset) combined with population numbers (from OECD QNA dataset). A more granular level of the consumption expenditures data on nondurables and service exists at the G7 and OECD constituent countries level. For each constituent country, I also calculate another measure of the per capita real consumption growth (ΔC_t) using seasonally adjusted volume estimates of consumption expenditures on nondurables and services combined with population numbers. Subsequently, I construct the G7 and OECD aggregates using real GDP weights. For seven advanced economies: the United States, the Euro Area, Japan, the United Kingdom, Switzerland, Canada, and Australia, I collect their Shadow Short Rate by Krippner (2013) via Haver Analytics. Long history of annual inflation, per capita real GDP growth, and per capita real consumption growth data for these seven advanced economies are collected from the Jordà-Schularick-Taylor (JST) Macrohistory Database Jordà et al. (2017). From 2017 onward, I update the macro data using the same source as the JST database. In the asset pricing tests, I measure equity market performance for each country using MSCI equity index data obtained from Datastream. I collect total return indices in US dollars. The sample period runs from March 1985 to September 2019, but the number of equity indices for which data are available varies over time. I convert daily data into non-overlapping monthly observations by sampling

²All the data used in this study are final/revised releases; therefore, they are not the data that is available in real time. This is because the primary purpose of this paper is to estimate a model of inflation and to infer the inflation risk premium. However, it is clear that the use of real-time data could affect the results.

³Details of seasonality adjustment can be found in Appendix A.2.1

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on the last business day of each month. The dataset covers 38 countries, and a full list of countries is available in Table A.1.

Table 1.1 presents descriptive statistics for the data mentioned above. The sample period for the first half of the paper is from June 1970 to September 2019, where the start of the sample period coincides with the available data for the OECD aggregate. A burn-in period of 60 quarters leaves a sample for asset pricing tests from March 1985 to September 2019.

Table 1.1 Descriptive statistics.

	Mean	Median	Std. Dev	AC1	Obs
Panel A: Quarterly Per Capita Real Consumption Growth (ΔC)					
G7 Non-durables and Service	1.87	1.84	0.81	0.48	198
G7 Private Consumption	2.61	2.65	0.99	0.38	198
OECD Non-durables and Service	1.89	1.88	0.79	0.50	198
OECD Private Consumption	2.72	2.78	0.90	0.45	198
USA Non-durables and Service	1.72	1.67	1.01	0.21	198
Panel B: Quarterly Seasonally Adjusted Inflation (Π_t)					
G7	3.90	3.19	1.57	0.79	198
OECD	3.85	2.76	1.61	0.89	198
USA	3.88	3.10	1.72	0.60	198
Panel C: Monthly Data					
$R_{f,t}$	3.23	3.24	0.73	0.98	414
$R_{m,t}$	13.59	18.40	17.89	0.16	414
$R_{m,t} - R_{f,t}$	10.36	14.64	17.86	0.16	414
Π_t	3.85	3.62	0.82	0.69	414
τ_t	4.03	3.43	0.67	0.88	414
$u_{\Pi,t}$	-0.18	-0.18	0.60	0.29	414

This table presents descriptive statistics for quarterly (quarter-on-quarter) consumption growth (ΔC_t) and inflation (Π_t) for G7, OECD and USA area from June 1970 to September 2019 in Panel A and B. In Panel C, this table also presents descriptive statistics for monthly US risk free rate ($R_{f,t}$), cross-section average stocks market total return index return in USD ($R_{m,t}$), market excess return ($R_{m,t} - R_{f,t}$), monthly (month-on-month) seasonally adjusted inflation (Π_t), trend inflation (τ_t) and inflation surprise ($u_{\Pi,t}$) for the OECD area from March 1985 to September 2019. Mean, median and standard deviation are expressed in annualised percentages. AC1 is the first-order auto-correlation coefficient. Obs is the number of observations.

1.3 The time-varying relation between inflation and consumption

1.3.1 Global phenomena

To analyse the conditional relation between current inflation and future real consumption growth, Boons et al. (2020) estimate a simple ordinary least squares (OLS) regressions of

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future consumption growth from time $t + 1$ on inflation over time t :

$$\Delta C_{t+1} = d_0^{u,1Q} + d_1^{u,1Q}\Pi_t + e_{t+1}. \quad (1.1)$$

Based on this model, the authors present evidence of an insignificant unconditional relation between current inflation and future consumption in the US. Nonetheless, they discuss evidence from Piazzesi et al. (2006) who demonstrate that historically, an increase in inflation is bad news for future consumption growth. Boons et al. (2020) propose a potential explanation for this seeming inconsistency that the unconditional regression conceals variation over time in the relationship between consumption and inflation.

To quantify the magnitude of this time variation, the authors further propose the following two-stage test:

$$\Delta C_{s+1} = a_t^{1Q} + b_t^{1Q}\Pi_s + e_{s+1}, \quad \text{for } s = 1, \dots, t-1, \quad (1.2)$$

$$\Delta C_{t+1} = d_0^{c,1Q} + d_1^{c,1Q}(\hat{a}_t^{1Q} + \hat{b}_t^{1Q}\Pi_t) + e_{t+1}. \quad (1.3)$$

In the first stage, Equation (1.2) regresses consumption growth on lagged inflation over a backwards-looking window using all data available up to time t . Hence, the expanding window s runs from 1 to $t - 1$. This regression is estimated using weighted least squares (WLS), where weights are given by an exponential weighting scheme that has a half-life converging to 5 years for large t .⁴ The authors argue that the expanding window ensures that one uses all the available information, whereas an exponential decay in weights assures that the most recent observations receive the largest weight. In the second stage, Equation (1.3) uses the estimated coefficients and inflation observed at time t (i.e. $\hat{a}_t^{1Q} + \hat{b}_t^{1Q}\Pi_t$) in predicting consumption growth at $t + 1$. This setup prevents the use of forward-looking information in the second stage of consumption growth prediction. Also, the absence of a look-ahead bias is a crucial premise to use the estimated first-stage coefficient b_t^{1Q} to predict various returns in the time series. If the two-stage structure correctly models the conditional expectation of consumption growth, one should find that $d_0^{c,1Q} = 0$ and $d_1^{c,1Q} = 1$, which is what the authors found in the US data.

To assess the international evidence on the relationship between inflation and consumption growth, I present in Table 1.2 results from estimating Equation (1.1) and Equation (1.3) using quarterly US and international aggregate data. In Panel A of Table 1.2, one can see that the unconditional relation between current inflation and future consumption at the US or international aggregate level (G7 and OECD) is positive but is not significantly different

⁴The number of observations depends on data frequency. The estimation converges to 60 observations for monthly data or 20 observations for quarterly data.

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from zero, as measured by the coefficient estimate for $d_1^{u,1Q}$.⁵ The insignificant coefficients at the international level are consistent with the US results.

Panel B of Table 1.2 presents the results for the two-stage model. To test significance, I report asymptotic Newey-West and bootstrapped t -statistics. The estimate of $d_1^{c,1Q}$ is significantly larger than zero and close to one for the US or international aggregate level. Additionally, for no model can one reject the hypothesis that $d_0^{c,1Q} = 0$, suggesting that the two-stage structure provides an unbiased estimate of the conditional expectation of consumption growth. In the second stage, the model captures an economically large share of the variation in consumption growth, with an adjusted R^2 that ranges from 17% for the US to 29% for the G7 aggregate level. Thus, the phenomena that inflation strongly predicts consumption growth when one accounts for the time-varying relation between these macro-variables exist in the US and globally.

The main proxy for the nominal-real covariance denoted as NRC_t henceforth, is the time-varying coefficient from the first stage regression in Equation (1.2) of 1-quarter consumption growth on lagged inflation, $\hat{b}_t^{1Q}$. Instead of using monthly data as in Boons et al. (2020), I further explore quarterly and annual frequency due to the international NRC_t estimation data limit. In robustness check, Figure 1.1 plots the US NRC_t estimated with different frequencies, including monthly, quarterly and yearly. In the left panel of Figure 1.1, we can see that the US NRC_t estimated using 1-quarter consumption growth on lagged quarterly quarter-on-quarter inflation closely tracks the estimates from 3-month consumption growth on lagged monthly month-on-month inflation. However, as shown in the right panel of Figure 1.1, at the annual frequency, the sign-switch characteristic in the US NRC_t disappears when estimated with 1-year consumption growth and lagged year-on-year yearly inflation. Instead, we can recover the sign-switch feature at the annual frequency by estimating the contemporaneous relation between consumption growth and inflation. Thus, the time-varying nominal-real covariance can be consistently captured using monthly or quarterly consumption growth and lagged inflation. If one is limited to the annual data frequency, contemporaneous regression of consumption growth on inflation is needed to manifest the time-varying nominal-real covariance.

⁵One can re-write Equation (1.1) in log terms as $\Delta c_{t+1}^N - \pi_{t+1} = d_0^{u,1Q} + d_1^{u,1Q} \pi_t + \varepsilon_{t+1}$, where Δc_{t+1}^N is the log nominal consumption growth. Thus, the covariance between real consumption growth and lagged inflation has two components. One depends on the correlation between nominal consumption growth and lagged inflation, and the other component is the serial correlation of inflation. Because inflation is strongly persistent, a positive and statistically significant $d_1^{u,1Q}$ could arise solely due to the serial correlation in the inflation series. To address this issue, Table A.2 reports the above-mentioned two correlation components. Indeed, the auto-correlation of inflation is high, ranging from 0.79 to 0.60 across different areas during the sample period from June 1970 to September 2019. However, the correlation between nominal consumption growth and lagged inflation is also substantially different from zero, ranging from 0.48 to 0.63. Thus, the predictive power of lagged inflation on real consumption growth is not solely driven by inflation persistence.

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Table 1.2 Unconditional and conditional predictive regressions of consumption growth on inflation.

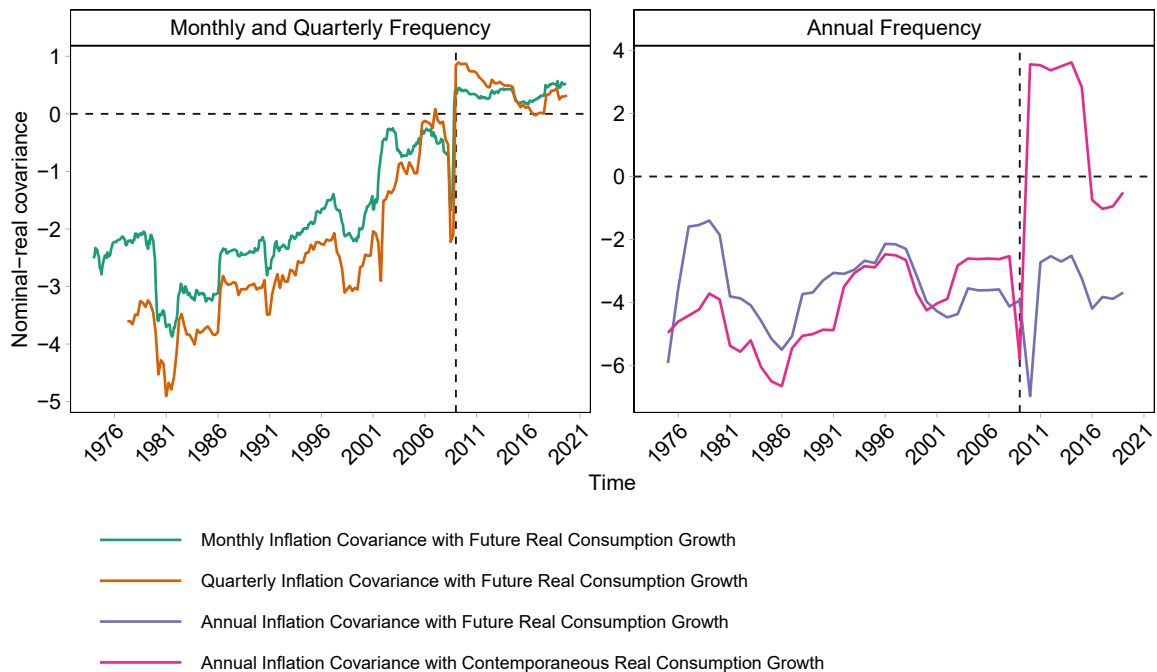
	US	G7		OECD	
	NS	NS	PC	NS	PC
Panel A: unconditional					
$d_0^{u,1Q}$	0.00	0.00	0.01	0.00	0.01
t	(5.22)	(4.78)	(6.77)	(4.11)	(6.50)
t_{boot}	(2.73)	(2.46)	(3.34)	(2.81)	(4.09)
$d_1^{u,1Q}$	0.02	0.10	0.05	0.08	0.09
t	(0.22)	(0.99)	(0.51)	(0.53)	(0.69)
t_{boot}	(0.23)	(1.06)	(0.54)	(0.83)	(0.97)
Observations	139	139	139	139	139
Adjusted R ²	-0.01	0.01	-0.00	0.00	0.00
Panel B: conditional					
$d_0^{c,1Q}$	-0.00	-0.00	-0.00	-0.00	-0.00
t	(-0.74)	(-0.55)	(-0.82)	(-0.51)	(-0.78)
t_{boot}	(-0.78)	(-0.52)	(-0.80)	(-0.57)	(-0.82)
$d_1^{c,1Q}$	1.03	0.95	1.03	0.95	1.09
t	(4.30)	(4.74)	(5.21)	(4.32)	(4.46)
t_{boot}	(3.50)	(3.60)	(4.01)	(3.75)	(3.90)
Observations	139	139	139	139	139
Adjusted R ²	0.17	0.27	0.29	0.28	0.27

This table presents the predictive regressions of quarterly consumption growth on lagged inflation from March 1985 to September 2019. The US quarterly per capita real consumption growth uses data from the NIPA Tables. The G7 universe and OECD universe aggregate use OECD data. I present two measures of the quarterly real consumption growth. One measure uses consumption expenditures on non-durables and services (NS) whereas the other measure uses private final consumption expenditures (PC). The Panel A presents an unconditional regression: $\Delta C_{t+1} = d_0^{u,1Q} + d_1^{u,1Q}\Pi_t + e_{t+1}$. Panel B presents a two-stage conditional regression. In the first stage, I regress consumption growth on lagged inflation over a backward-looking rolling window, $\Delta C_{s+1} = a_t^{1Q} + b_t^{1Q}\Pi_s + e_{s+1}$, for $s = 1, \dots, t - K$. Combining the estimated coefficients with inflation in quarter t , I then predict future consumption growth in the full sample: $\Delta C_{t+1} = d_0^{c,1Q} + d_1^{c,1Q}(\hat{a}_t^{1Q} + \hat{b}_t^{1Q}\Pi_s) + e_{t+1}$. We report t -statistics using Newey-West standard errors with optimal lags and bootstrapped t -statistics using standard errors calculated as the standard deviation of coefficient estimates in 1000 bootstrap replications.

Figure 1.2 plots the quarterly estimates of nominal-real covariance, $\hat{b}_t^{1Q}$, for the US, G7 aggregate and OECD aggregate universe. The nominal-real covariance in the US was negative on average in the period pre-2009. It was unusually low in the early 1980s and approaching positive in the early 2000s. Then, the US NRC_t turned positive during the

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Fig. 1.1 US nominal-real covariance at different frequencies.



Alternative measures of the US nominal-real covariance with different data frequency. Each of the measures includes the coefficient on a rolling regression of future or contemporaneous consumption growth on inflation.

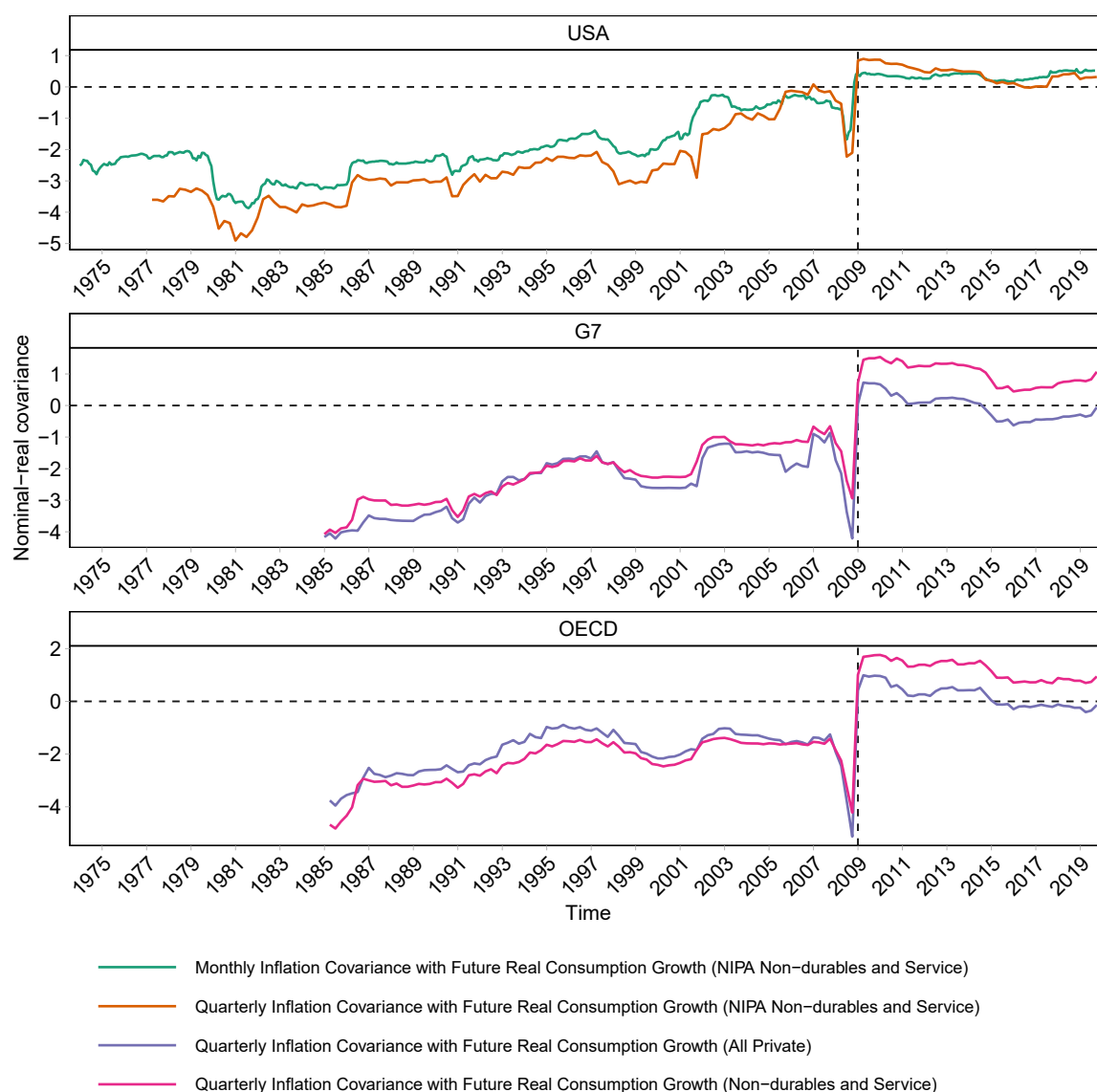
downturns of 2007-09 and stayed positive during the zero lower bound era until 2015. The time-variation in the US nominal-real covariance has been discussed in the literature on the shift in the US stock-bond correlation (see Campbell et al., 2017). Thus, this paper extends the analysis to international data. Figure 1.2 examines the nominal-real covariance across G7 and OECD universe. I show that similar to the US result, the global NRC_t has increased since the 1980s and turned positive during the zero lower bound era from 2009 to 2015. In the remainder of this paper, I analyse empirically and theoretically what rationalises the global time-variation in inflation risk, measured by nominal-real covariance, and its asset pricing implications.

1.3.2 The driver of the time variation

To answer what drives fluctuations in the cyclical properties of global inflation, we need to start by answering what drives global inflation. Central banks worldwide have adopted inflation targeting, a technique intimately linked to the New Keynesian macroeconomic models. In this framework, inflation is determined because the central banks systematically raise or lower nominal interest rates more than one-for-one with the inflation movement.

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Fig. 1.2 Alternative measures of the nominal-real covariance with different country universes.



Each of the measures includes the coefficient on a rolling regression of consumption growth on 1-quarter lagged inflation. The US monthly (quarterly) per capita real consumption growth uses data from the NIPA Tables. The G7 universe and OECD universe aggregate use OECD data. I present two measures of the quarterly real consumption growth. One measure uses consumption expenditures on nondurables and services whereas the other measure uses private final consumption expenditures.

Long treated as the main policy instrument by the central bank, the interest rate was not available as a tool for macroeconomic stabilisation in the presence of a lower bound following the 2008 financial crisis. This lower bound led to a breakdown of the relationship between policy rates and inflation and, therefore, is a natural suspect that drives the fluctuations in the cyclical properties of inflation.

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Indeed, the models proposed in Song (2017) and Campbell et al. (2020) suggest that the feasibility with which the Federal Reserve steers actual inflation toward the inflation target, together with a change in the nature of macroeconomic shocks, are responsible for the variations in the cyclical properties of inflation and the stock-bond correlation. In this paper, the central intuition of the sign-switching process in the NRC_t is further inspired by the mechanism discussed in Bilal (2018). Under a New Keynesian framework, the presence of a lower bound generates a new source of macroeconomic risk: the risk that the zero lower bound will bind in the future when interest rate policy is no longer available as a stabilisation tool.

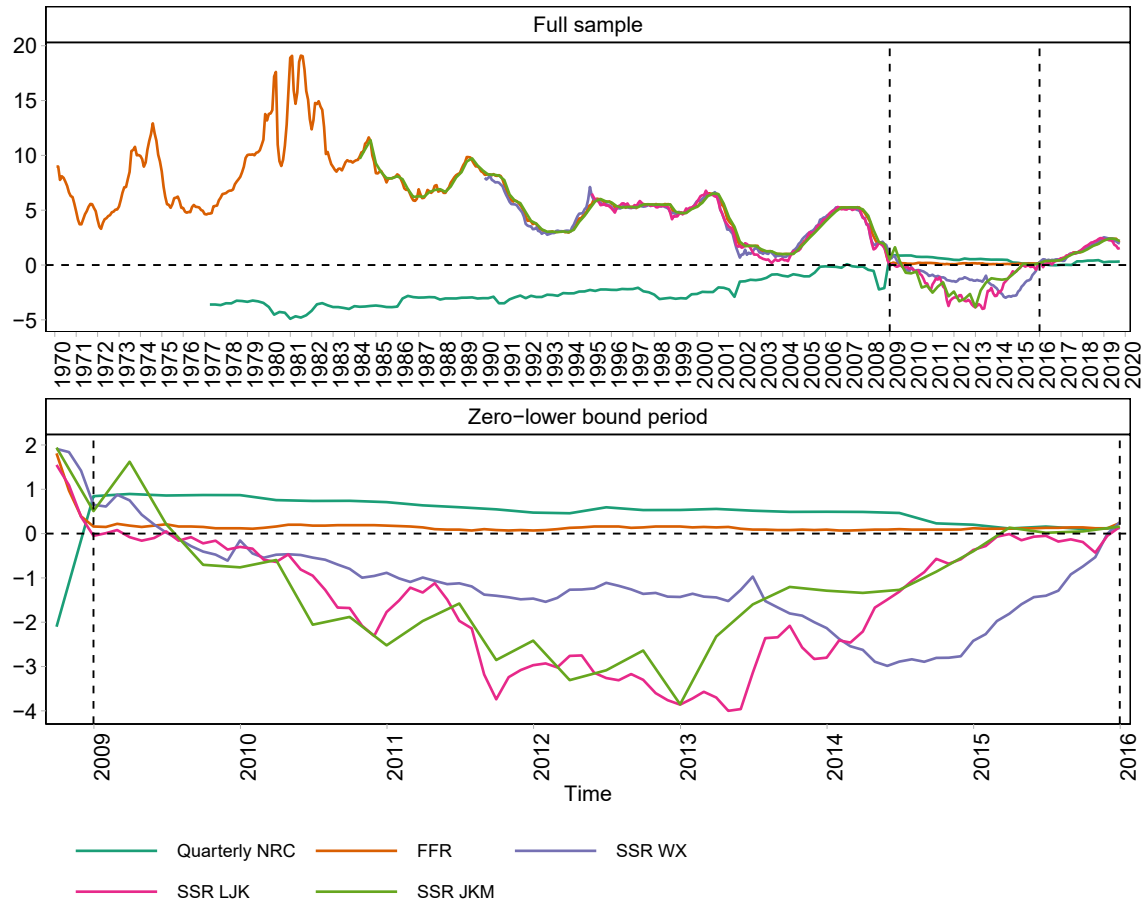
The relation with the zero lower bound

To illustrate the relation between the cyclical property of inflation and the zero lower bound, I start by plotting the nominal-real covariance and indicators of ZLB (i.e. the policy rates and shadow rates) side-by-side. I show that the sign-switching covariance in the US and worldwide coincided with the onset of the low rate environment in December 2008, when the capacity of the traditional stabilisation policy became limited. Indeed, Figure 1.3 plots the US NRC_t against the Federal Fund Rate (FFR) and three measures of the Shadow Short Rate (SSR): SSR WX by Wu and Xia (2016), SSR LJK by Krippner (2013) and SSR JKM by Jones et al. (2021). The official "zero lower bound" environment is defined to be the period between 16 December 2008 and 15 December 2015 when the Federal Open Market Committee has targeted the federal funds rate between 0 and 0.25 per cent. We can see that the US NRC_t switched into the positive domain precisely in December 2008 and converged back to zero in December 2015, which coincides perfectly with the sign-switch in the three measures of the shadow rate.

Beyond the US result, Krippner (2013) also provide shadow rates for the Euro Area, Japan, the United Kingdom, Switzerland, Canada, and Australia. Figure 1.4 plots the country-level contemporaneous NRC_t s against their corresponding shadow rates. Using contemporaneous estimation, I trade away the conditional relationship for more extended data availability at the annual frequency. Even with the contemporaneous relationship, we can see the US NRC_t and the shadow rate switch sign simultaneously at the start and the end of the zero lower bound era. Additionally, the Euro Area, Switzerland and Canada all have historically negative NRC_t on average. Like the US, these three economies' NRC_t s have been increasing as their shadow rates decreased and these NRC_t also experienced a sign-switch as their shadow rate entered the negative domain. Interestingly, the sign-switch in the NRC_t of Japan happened in the early 1990s as Japan's shadow rate has been restrained in the negative territory since then. On the contrary, the NRC_t of Australia has yet to experience any significant jump as the Australian

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Fig. 1.3 US nominal-real covariance and the shadow short rate.



The evolution of nominal-real covariance and the shadow short rate in the US. This figure presents three measures of the US shadow short rate (annualised and in per cent unit), including Krippner (2013), Wu and Xia (2016) and Jones et al. (2021). The nominal-real covariance is estimated using NIPA Tables data on the monthly (quarterly) real consumption (GDP) growth and lagged monthly (quarterly) inflation.

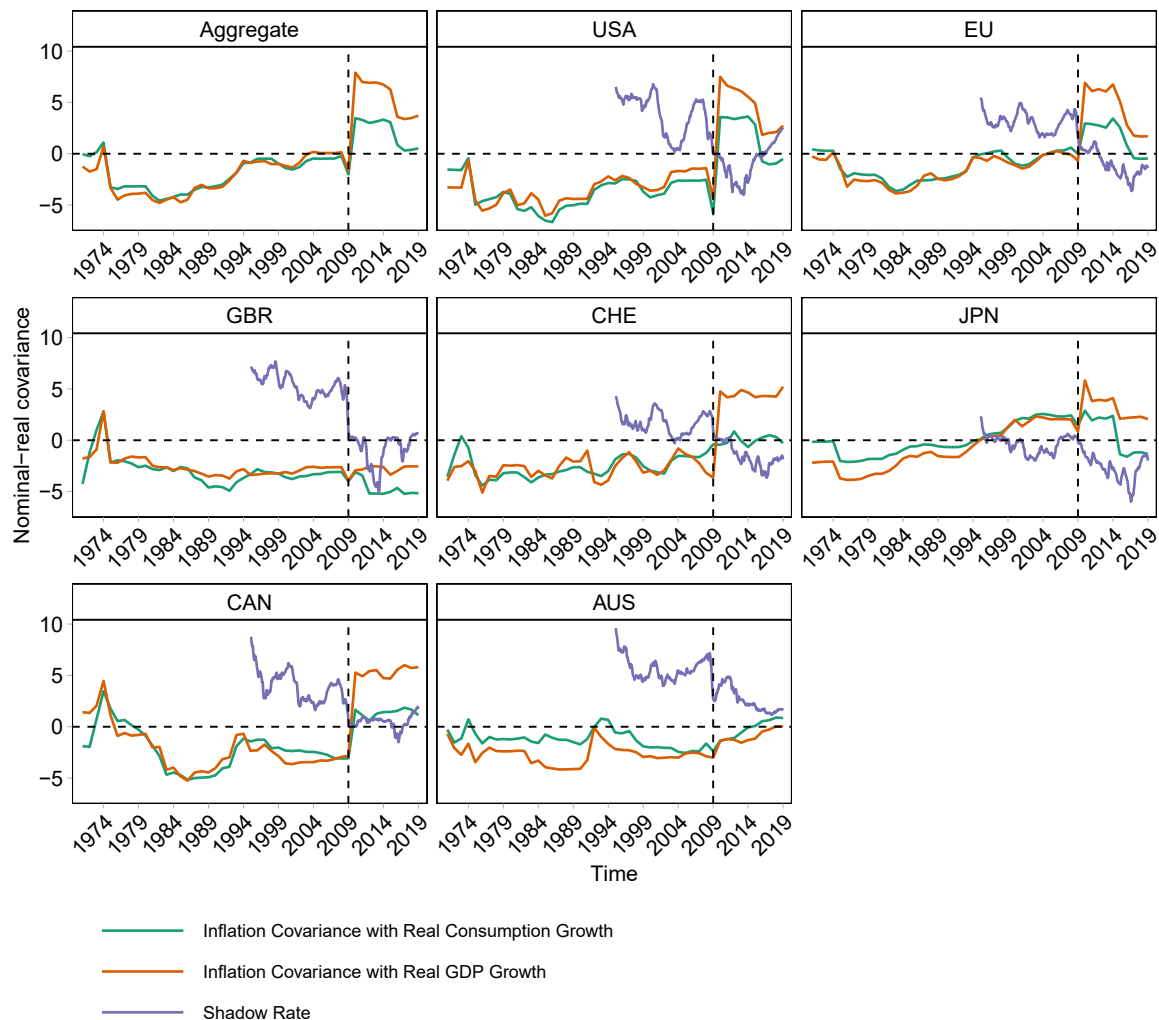
interest rate remains sufficiently positive. Despite the exception in the United Kingdom, it is fair to claim that the time-varying shadow short rate coincides with the sign-switch in the nominal-real covariance around the world's major economy.

Intuition for the sign-switching process

In this section, I formally elaborate on how the zero lower bound shifts the co-movement of future consumption growth and inflation. Theoretically, far from the ZLB, demand shocks have little effect because changes in the monetary policy rate neutralise demand fluctuations; thus, the relative importance of supply shocks increases. Positive supply shocks increase consumption but decrease inflation. Dominating supply shocks give rise to a negative

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Fig. 1.4 Nominal-real covariance and the shadow short rate around the world.



The evolution of nominal-real covariance and the shadow short rate around the world. This figure presents the LJK shadow short rate of Krippner (2013) (in monthly and per cent unit) for the major central bank around the world. The nominal-real covariance is estimated using contemporaneous JST annual data on real consumption (GDP) growth and inflation.

covariance between inflation and consumption growth. However, when the ZLB binds or is close to binding, demand shocks are amplified because they are no longer (or difficult) to be counteracted by a change in the interest rate. A positive demand shock increases both consumption and inflation. Opposite to the supply shock, a dominating demand shock gives rise to a positive covariance between consumption growth and inflation.

To provide empirical examples of the mechanism mentioned above, I estimate the role of the different shocks in driving the US (i) inflation, (ii) unemployment, (iii) and federal funds rate from 1960 to 2019 in Appendix A.1. Figure A.4 to A.6 present the historical

1.3 The time-varying relation between inflation and consumption

decomposition of the three variables, showing the estimated contribution of each shock to deviations of the variables from their steady state at each point in time. It is clear that supply shocks were particularly important during the 1970s and that the contribution of monetary policy shocks (offsetting demand shocks) was particularly relevant during the Volcker era from 1979-1982. Thus, the dominating supply shocks are manifest in the unusually low US NRC_t in the early 1980s in Figure 1.3.

However, in Figure A.4 to A.6, the post-2000 decade was characterised by an environment in which large supply shocks were absent, and demand shocks drove the major recessions as the interest rate remained low following the dot-com bubble. Indeed, we can see the opposite effect of supply and demand shock in the increasing US NRC_t from the late 1990s to the early 2000s in Figure 1.3. Furthermore, the most significant jump in the NRC_t coincided with the 2008-2009 financial crisis, which appeared as a particularly large demand shock accompanied by zero lower bound limitation, as shown in the historical shocks decomposition.

To summarise, as the changing expected duration of the zero lower bound varies the feasibility of the traditional stabilisation policy in neutralising the demand shocks, the cyclical properties of inflation fluctuate correspondingly. Inflation is counter-cyclical away from the ZLB, which gives rise to a negative NRC_t ; however, at the ZLB, inflation is pro-cyclical; hence the NRC_t is positive.

Modelling the sign-switching process

To formally test the role of the expected duration of the zero lower bound, I model the process for the nominal-real covariance, NRC_{t+1} , as an AR(1) process with time-varying intercept:

$$\begin{aligned} NRC_{t+1} &= \alpha_t + \beta_1 NRC_t + \varepsilon_{t+1}, \\ \alpha_t &\equiv \beta_0 + \beta_2 I_t, \end{aligned} \tag{1.4}$$

where the persistence of NRC_{t+1} is driven by the auto-regressive component NRC_t , and the level of NRC_{t+1} is driven by the time-varying intercept α_t , which is a function of a state variable: the expected duration of the zero lower bound. I proxy the expected duration of the zero lower bound using (i) the level of the Federal Fund Rate (I_t^{FFR}) (ii) or the structural Shadow Short Rate (I_t^{SSR}) by Jones et al. (2021). While the FFR is a natural proxy for the probability of a binding ZLB constraint, it does not vary at zero. Thus, the unconstrained shadow rate is a better measure of the expected duration and the severity of the ZLB episode. I use the structural SSR *à la* Jones et al. (2021) and Jones et al. (2022) because it is precisely based on decomposing the expected length of the ZLB period into its underlying sources. Specifically, Jones et al. (2021) argue that shadow rate term structure models do

not disentangle movements in the term structure due to unconventional policies from those due to other shocks. For example, output and expected inflation might fall after a negative shock, whose effect is similar to a tighter monetary policy that increases the expectation of a binding ZLB and the shadow rate. Nevertheless, output and inflation might increase after a ‘lower-for-longer’ (expansionary) announcement extending the fixed-interest-rate regime but implying a decrease in the shadow rate. Thus, to capture the policy stance given economic conditions, it is critical to uncover the underlying determinants of the duration.

Table 1.3 presents the results from simple OLS regression of Equation (1.4). To test significance, I report asymptotic Newey-West and bootstrapped t -statistics. In Columns 1 and 4, I do not include the auto-regressive component NRC_t and find that both FFR (I_t^{FFR}) and the structural SSR (I_t^{SSR}) are significant negative predictors for the time-variation in the nominal-real covariance. In Columns 2 and 5, I include the NRC_t , and the estimated coefficients on the two ZLB duration proxies are still negative and significant. Since the FFR and structural SSR are negatively related to the length of the ZLB episode, these estimations indicate that nominal-real covariance is increasing in the expected ZLB duration. This result is in line with the large negative NRC_t in the early 1980s when interest rates were high and far from ZLB and the jump in the NRC_t in December 2008 when the FFR entered the ZLB range while the SSR indicates a binding ZLB constraint.

In Columns 3 and 6, I include an interactive term between the rate variable I_t and a ZLB dummy variable that equals one between December 2008 and December 2015 and zero otherwise. The estimated coefficients for the ZLB dummy interactive terms are insignificant, indicating that the simple setup in Equation (1.4) is sufficient in capturing the time variation in the nominal-real covariance. Indeed, Figure 1.5 plots the predicted value of α_t in Equation (1.4). Even without the auto-regressive component NRC_t , the expected ZLB duration component is sufficient to deliver the time-varying characteristic of the nominal-real covariance. The following section explores the asset pricing implications of the time-variation inflation risk driven by the nominal-real covariance.

1.4 The time-varying global inflation risk premium

This section examines whether the global inflation risk premium fluctuates over time in a manner consistent with the global nominal-real covariance’s time variation.

1.4.1 Estimating the global inflation risk premium

I first describe the method to estimate the global inflation risk premium.

1.4 The time-varying global inflation risk premium

Table 1.3 Predicting the nominal-real covariance with interest rate.

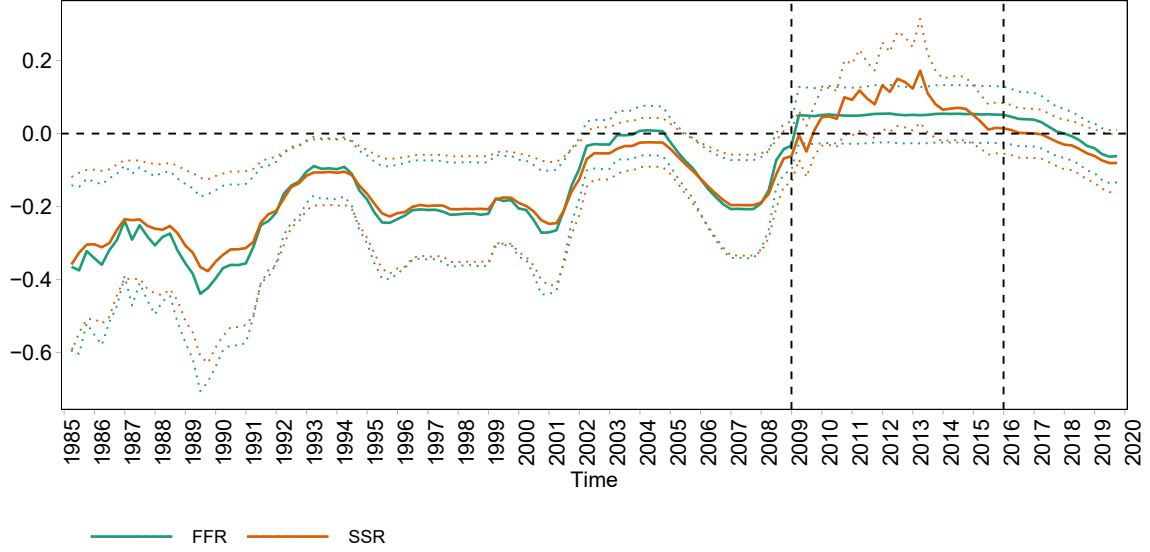
	(1)	(2)	(3)	(4)	(5)	(6)
α_t	0.24	0.06	0.07	-0.09	0.02	0.06
t	(1.15)	(1.08)	(0.85)	(-0.50)	(0.51)	(1.05)
t_{boot}	(0.55)	(0.84)	(0.76)	(-0.28)	(0.27)	(0.80)
I_t^{FFR}	-0.45	-0.05	-0.05			
t	(-11.48)	(-1.88)	(-1.80)			
t_{boot}	(-6.82)	(-2.20)	(-2.18)			
$I_t^{FFR} \times D^{ZLB}$			-0.13			
t			(-0.28)			
t_{boot}			(-0.22)			
I_t^{SSR}				-0.38	-0.04	-0.05
t				(-13.32)	(-1.85)	(-1.95)
t_{boot}				(-8.85)	(-2.48)	(-2.12)
$I_t^{SSR} \times D^{ZLB}$						0.06
t						(1.56)
t_{boot}						(1.56)
NRC_t		0.89	0.89		0.89	0.89
t		(17.83)	(17.91)		(17.94)	(17.80)
t_{boot}		(18.11)	(15.74)		(19.71)	(16.92)
Observations	139	139	139	139	139	139
Adjusted R ²	0.70	0.95	0.95	0.70	0.95	0.95

This table presents the predictive regressions of quarterly nominal-real covariance on lagged Federal Fund Rate and Shadow Short Rate by Jones et al. (2021), from March 1985 to September 2019. The process for the nominal-real covariance NRC_{t+1} is modelled as an AR(1) process with time-varying intercept: $NRC_{t+1} = \alpha_t + \beta_1 NRC_t + \varepsilon_{t+1}$, where $\alpha_t \equiv \beta_0 + \beta_2 I_t$, NRC_t is the auto-regressive component, the time-varying intercept α_t is a function of the lagged Federal Fund Rate I_t^{FFR} or the lagged Shadow Short Rate I_t^{SSR} . In Columns 1 and 4, I do not include the auto-regressive component NRC_t . In Columns 3 and 6, I further include an interactive term between the rate variable I_t and a zero-lower-bound dummy variable that equals one during December 2008 and December 2015 and zeroes otherwise. To test significance, the asymptotic Newey-West and bootstrapped t -statistics are both reported in parentheses.

Inflation betas

At the end of each sample month t , I measure the inflation exposure of country i by estimating its historical beta of excess returns, $R_{i,t}$, with respect to monthly innovations in inflation. Following Stock and Watson (2007) and Stock and Watson (2016), I filter out these inflation surprises, denoted $u_{\Pi,t}$, using an unobserved components model with stochastic volatility.

Fig. 1.5 The time-varying intercept of the US nominal-real covariance.



The time-varying level (intercept) of the nominal-real covariance. This figure presents the predicted value of α_t for the model $NRC_{t+1} = \alpha_t + \beta_1 NRC_t + \varepsilon_{t+1}$, where $\alpha_t \equiv \beta_0 + \beta_2 I_t$. The α_t is driven by either the Federal Fund Rate, I_t^{FFR} , or the Shadow Short Rate, I_t^{SSR} . I also present the 90% confidence intervals.

The model is estimated in "pseudo-real-time" using expanding windows. Details of the estimation can be found in Appendix A.2.2.

The literature on inflation hedging models asset returns to depend on expected and unexpected inflation (e.g. Fama and Schwert, 1977; Schwert, 1981; Schotman and Schweitzer, 2000). Specifically, the strength of the Fisher relation is measured by the relation between expected inflation and asset returns. Then, the inflation beta of an asset indicates how its prices adjust instantaneously to unexpected inflation. Furthermore, to motivate the later theoretical discussion, I directly model the inflation beta to be linear in 1-quarter lagged nominal-real covariance, $\beta_{\Pi,i,t} = \beta_{\Pi,i,t}^0 + \beta_{\Pi,i,t}^1 NRC_{t-1}^Q$.

The estimator of an equity's inflation exposure, $\beta_{\Pi,i,t} = \beta_{\Pi,i,t}^0 + \beta_{\Pi,i,t}^1 NRC_{t-1}^Q$, is then given by:

$$R_{i,t} = \alpha_{i,t} + (\beta_{\Pi,i,t}^0 + \beta_{\Pi,i,t}^1 NRC_{t-1}^Q) u_{\Pi,t} + \beta_{\tau,i,t} \tau_{t-1} + e_{i,t}, \quad (1.5)$$

where $R_{i,t}$ is the simple equity excess return, τ_{t-1} is the expected inflation as of month $t-1$, $u_{\Pi,t} = \pi_t - \tau_{t-1}$ is the unexpected inflation for month t . Note that I use the OECD inflation and the NRC_t estimated with OECD inflation and consumption growth. Empirically, the historical inflation beta in Equation (1.5) is estimated in a manner similar to Boons et al. (2020) using a WLS regression with exponential weights (half-life converging to 60 months)

1.4 The time-varying global inflation risk premium

over an expanding window that uses all observations from the first month of the equity index included in the sample up to month t . I require that equity indices have at least 24 out of the last 60 months of return available. I also transform the estimated $\hat{\beta}_{\Pi,i,t}$ using a Vasicek (1973) adjustment

$$\hat{\beta}_{\Pi,i,t}^v = \hat{\beta}_{\Pi,i,t} + \frac{var_{TS}(\hat{\beta}_{\Pi,i,t})}{[var_{TS}(\hat{\beta}_{\Pi,i,t}) + var_{CS}(\hat{\beta}_{\Pi,i,t})]} \times [mean_{CS}(\hat{\beta}_{\Pi,i,t}) - \hat{\beta}_{\Pi,i,t}]. \quad (1.6)$$

Thus, each $\hat{\beta}_{\Pi,i,t}^v$ is a weighted average of the equity index's beta estimated in the time-series and the average of all betas in the cross-section of the month t , $mean_{CS}(\hat{\beta}_{\Pi,i,t})$. From this point forward, inflation betas return to the WLS and Vasicek-adjusted betas, and I drop the hat and superscript v .

Inflation portfolios

Each month I create five portfolios by sorting all country equity indices based on 1-month lagged inflation betas, and these portfolios are held for one month. The one-fifth of all available indices in a given month that has the lowest lagged inflation beta are allocated to the first portfolio (denoted PL), the next fifth is allocated to portfolio 2, and so on, and the one-fifth of all indices with the highest lagged inflation beta is allocated to the fifth portfolio (denoted PH). I compute the excess return for each portfolio as an equally weighted average of the equity indices' excess returns within that portfolio. Hence, this procedure yields a time series of five equity portfolios' excess returns. I require that the cross-section have at least 30 equity indices, together with a burn-in period of 60-month; this results in a sample of post-ranking returns from February 1995 to September 2019.

The global inflation risk premium

I use two standard approaches to measure the global inflation risk premium (IP_t). The first estimate of the inflation risk premium is the difference in excess return between the High and Low inflation beta-sorted portfolios (denoted IP_t^{HL}).

The second estimate of the inflation risk premium is the return of a Asness et al. (2013) rank-weighted portfolio (denoted IP_t^{RW}), where the portfolio weights are proportional to the lagged inflation beta. Mathematically, the weights are

$$w_{i,t}^{Rank} = c_t \left(\text{rank}(\beta_{\Pi,i,t}) - \text{med}\{\text{rank}(\beta_{\Pi,j,t})\} \right),$$

$$\text{where } c_t = \frac{2}{\sum \left| \text{rank}(\beta_{\Pi,i,t}) - \text{med}\{\text{rank}(\beta_{\Pi,j,t})\} \right|}. \quad (1.7)$$

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The term c_t is a scaling factor such that the absolute sum of all portfolio weights equals two so that we are one dollar long and one dollar short as in the long-short portfolio case. The term $\text{med}\{\text{rank}(\beta_{\Pi,j,t})\}$ indicates the median of the rank in the cross-section at time t . Again, I take no position in the median inflation exposure equity index. Given this construction, the rank-weighted portfolios are also long-short portfolios with no direct dollar exposure.

Ex post inflation exposures

Table 1.4 presents descriptive statistics for the set of five inflation beta-sorted portfolios, the two estimates of the inflation risk premium: IP_t^{HL} and IP_t^{RW} , as well as the average portfolios of the five inflation beta-sorted portfolios (denoted IP_t^{Mean}). Panel A reports ex-ante and ex-post inflation exposures. The ex-post inflation exposures are estimated with a simple OLS regression of portfolio returns on unexpected inflation, controlling expected inflation over the full sample. The ex-post exposures line up monotonically from PH to PL, resulting in a large post-ranking beta of 2.47 for IP_t^{HL} . This dispersion has a similar magnitude to the ex-ante exposure. When $u_{\Pi,t}$ increases by one standard deviation (0.60 as shown in Table 1.1), a beta value of 2.47 corresponds to an average monthly return increase of 43 basis points. In comparison, the cross-section average portfolio (IP_t^{Mean}) with an inflation beta of 1.83 gains 32 basis points on average for the same increase in $u_{\Pi,t}$. The ex-post exposure is also significant for the rank-weighted portfolio measure of the inflation risk premium.

1.4.2 The inflation risk premium conditional over subsample

This section performs a sample split analysis motivated by the fact that the OECD nominal-real covariance, NRC_t , turned positive during the 2009 GFC without falling below its previous level again until the end of the sample (see Figure 1.2). I present in Panel B and C of Table 1.4, respectively, the inflation risk premium over the full sample as well as two subsamples split around 2009. I analyse annualised average excess returns, Sharpe ratio, and Fama-French three-factor alpha.

Over the full sample, average returns for the inflation beta-sorted portfolios decrease from 10.39% for the low beta portfolio to 4.81% for the high beta portfolio. This dispersion translates to a marginally significant return for IP_t^{HL} equal to -5.57% ($t = -2.26$). This effect is similar in both magnitude and significance for IP_t^{RW} and in alpha. This unconditional inflation risk premium corresponds to a Sharpe ratio around -0.45, whose absolute magnitude is comparable to the Sharpe ratio of the average international equity market, IP_t^{Mean} .

Boons et al. (2020) argue that a moderate and merely marginally significant unconditional US inflation risk premium conceals important variation over time that is driven by the

1.4 The time-varying global inflation risk premium

Table 1.4 Characterising inflation beta sorted portfolio and the inflation risk premium.

	L	2	3	4	H	IP^{HL}	IP^{RW}	IP^{Mean}
Panel A: Ex post inflation exposures								
Mean $\hat{\beta}_{\Pi,t}$	-3.32	-2.59	-2.12	-1.66	-0.89	2.43	1.98	-2.12
Ex-post $\hat{\beta}_{\Pi,p}$	0.86	1.25	1.31	2.67	3.33	2.47	2.06	1.89
t	(0.36)	(0.59)	(0.58)	(1.04)	(1.18)	(2.00)	(2.05)	(0.84)
Panel B: The Inflation risk premium (full sample)								
Avg. ret	10.39	9.14	6.98	7.95	4.81	-5.57	-4.56	7.85
t	(2.21)	(1.95)	(1.47)	(1.65)	(1.10)	(-2.26)	(-2.29)	(1.79)
Sharpe	0.53	0.45	0.35	0.39	0.25	-0.45	-0.47	0.42
α_{FF3}	2.22	0.48	-1.35	-0.83	-3.71	-5.93	-4.87	-0.64
t	(0.77)	(0.15)	(-0.47)	(-0.28)	(-1.36)	(-2.43)	(-2.56)	(-0.25)
Nobs	294	294	294	294	294	294	294	294
Panel C: The Inflation risk premium in subsamples								
Pre 2009								
Avg. ret.	10.21	8.45	4.54	4.54	0.88	-9.33	-8.11	5.72
t	(1.47)	(1.21)	(0.65)	(0.63)	(0.13)	(-2.83)	(-3.34)	(0.88)
Sharpe	0.50	0.38	0.22	0.21	0.04	-0.77	-0.84	0.29
α_{FF3}	6.63	5.26	0.90	0.77	-3.64	-10.27	-8.91	1.98
t	(1.69)	(1.32)	(0.23)	(0.14)	(-1.13)	(-3.15)	(-3.96)	(0.49)
Nobs	168	168	168	168	168	168	168	168
Post 2009								
Avg. ret.	10.62	10.07	10.22	12.51	10.06	-0.56	0.16	10.70
t	(1.85)	(1.84)	(1.81)	(2.13)	(1.79)	(-0.16)	(0.06)	(2.06)
Sharpe	0.58	0.57	0.57	0.68	0.55	-0.04	0.02	0.63
α_{FF3}	-5.18	-6.50	-7.28	-4.81	-6.62	-1.44	-0.76	-6.08
t	(-1.37)	(-1.75)	(-2.11)	(-1.23)	(-1.72)	(-0.40)	(-0.26)	(-1.86)
Nobs	126	126	126	126	126	126	126	126
Post-minus-Pre-2009 difference								
Avg. ret.	0.40	1.62	5.68	7.97	9.18	8.78	8.27	4.97
t	(0.05)	(0.20)	(0.65)	(0.90)	(1.11)	(1.89)	(2.24)	(0.61)
Sharpe	0.09	0.19	0.36	0.48	0.51	0.72	0.86	0.34
α_{FF3}	-11.80	-11.75	-8.18	-5.58	-2.98	8.83	8.15	-8.06
t	(-2.26)	(-1.99)	(-1.49)	(-0.87)	(-0.62)	(1.93)	(2.21)	(-1.69)
Nobs	294	294	294	294	294	294	294	294

This table presents the set of five inflation beta-sorted portfolios and their resulting estimates of the inflation risk premium, denoted IP^{HL} and IP^{RW} . IP^{HL} is the High-minus-Low inflation beta portfolio from the sort. IP^{RW} is the rank-weighted portfolio where the weights are proportional to the lagged inflation beta. I also report the average portfolio of the five inflation beta-sorted portfolios (denoted as IP^{Mean}). Panel A presents the average lagged inflation beta used for the sort, and the ex-post inflation betas, Ex-post $\hat{\beta}_{\Pi,p}$, that are estimated with a simple OLS regression of portfolio returns on unexpected inflation, controlling expected inflation over the full sample. t -statistics are in parentheses and use Newey-West standard errors. Next, I present annualised performance statistics (average returns, Sharpe ratio, and Fama-French three-factor alpha) and the number of observations over the full sample from February 1995 to September 2019 (Panel B) and split around March 2009 (Panel C). Panel D presents the post-2009 minus pre-2009 differences. For average returns and alphas, I present the t -statistics using Newey-West standard errors.

nominal-real covariance and, in particular, its recent reversal. Though the unconditional estimate of the global inflation risk premium is also modest in magnitude, this does not imply that the inflation risk is economically unimportant in the international equity market. To demonstrate this, Panel C shows a considerably larger and strongly statistically significant inflation risk premium in the pre-2009 subsample. Average returns for IP_t^{HL} and IP_t^{RW} are -9.33% and -8.11%, respectively, with t -statistics of -2.83 and -3.34. These average returns amount to a Sharpe ratio of -0.77 to -0.84, which is significantly higher than the average equities market's price of risk (in absolute value). Average returns are decreasing in inflation beta from 10.21% for PL to 0.88% for PH. Similar results for alphas suggest that the Fama-French three-factor model does not price the cross-section of global inflation portfolios in this subsample.

The inflation risk premium has seen a significant change since 2009. With average returns no longer decreasing with inflation beta, the High-minus-Low portfolio's average return was -0.56 per cent and the rank-weighted portfolio's average return was 0.16 per cent.⁶ These estimates are not statistically significant over the short sample of 10 years and are negligible economically, similar to the results for the US in Boons et al. (2020). The two Fama-French alphas are also small and insignificant. The evidence thus points to a much different inflation premium post-2009 than it did prior to 2009, one that is less in magnitude and sometimes even positive.

The differences between post-2009 and pre-2009 estimations are displayed in the last panel of Table 1.4. From PH to PL, average returns and alphas monotonically decline from 9.18% to 0.40% and 2.98% to -11.80%, respectively. Moreover, the post-minus-pre-2009 differences in IP_t^{HL} and IP_t^{RW} are economically large and significant.

In short, global evidence is broadly consistent with the time-varying US inflation risk premium discussed in Boons et al. (2020). I find that the global inflation risk premium has increased markedly over time, consistent with the global nominal-real covariance turned positive since 2009 from a negative state (on average since 1985).

1.4.3 The global inflation risk premium conditional on the nominal-real covariance

Boons et al. (2020) also employ predictive regressions as a sample split provides only a crude measure of how much the inflation risk premium varies over time. In a similar vein, I regress excess returns of the inflation portfolios (compounded over horizons K of one to four

⁶The same observation is also illustrated in Figure A.9 where I plot the cumulative excess return of inflation beta-sorted portfolios.

1.4 The time-varying global inflation risk premium

quarters) on NRC_t using:

$$R_{p,t+2+K} = L_0 + L_{NRC}NRC_t + \varepsilon_{t+2+K}. \quad (1.8)$$

I skip the most recent quarter return (i.e. skip R_{t+1}) when compounding the left-hand side returns to avoid look-ahead bias in the NRC_t estimation. NRC_t is standardised to accommodate the interpretation with a mean equal to zero and a standard deviation equal to one. This means that L_0 measures the average excess return of the corresponding portfolio, or the unconditional inflation risk premium, whereas L_{NRC} indicates the increase in annualised portfolio return for a one standard deviation rise in the nominal-real covariance. For each horizon, Table 1.5 presents the estimated coefficients (annualised), both asymptotic Newey-West and bootstrapped t-statistics, and the R^2 for the individual beta-sorted portfolios, the two estimates of the inflation risk premium (IP_t^{HL} and IP_t^{RW}), and the average portfolio across the individual beta-sorted portfolios (IP_t^{Mean}).

Consistent with the US results, the effect of NRC_t on the global inflation risk premium is positive, economically large, and statistically significant (based on both asymptotic and bootstrap inference). The inflation risk premium as calculated using IP_t^{HL} and IP_t^{RW} increases by roughly 4.5% to 4.8% for $K = 1Q$ for a one standard deviation increase in the nominal-real covariance. This increase is relative to an unconditional inflation risk premium of about -4.4% to -5.5%. At longer time horizons, the effect becomes stronger, increasing to almost 6% for $K = 3Q$ and 5.4% for $K = 4Q$. The R^2 are likewise increasing in the horizon, rising from about 4% for $K = 1Q$ to over 20% for $K = 4Q$. Finally, one can observe that L_{NRC} is increasing monotonically from low to high inflation beta by looking at the individual beta-sorted portfolios.

To summarise, complementary to the US results, I find international evidence that the inflation risk premium is strongly time-varying as the global nominal-real covariance fluctuates. The economic intuition for this finding is that when inflation is counter-cyclical, as it traditionally has been, country equity indices with high inflation beta are appealing as a means of hedging consumption risk. However, these same country equity indices are no longer desirable as a hedge anymore. They could even expose investors to additional consumption risk once the nominal-real covariance turns positive, as it does post-2009. Moreover, the sample split results around 2009 also support the proposed mechanism in the previous section that relies on the interest rate at or near the ZLB.

Time-Varying Global Inflation Risk and the Zero Lower Bound

Table 1.5 Predicting the inflation risk premium with the nominal-real covariance.

	L	2	3	4	H	IP^{HL}	IP^{RW}	IP^{Mean}
Panel A: K = 1Q								
L_0	10.67	9.70	7.40	8.26	4.81	-5.51	-4.39	8.13
t	(2.14)	(1.90)	(1.51)	(1.70)	(1.20)	(-2.40)	(-2.32)	(1.82)
t_{boot}	(3.00)	(2.62)	(2.06)	(2.34)	(1.30)	(-1.64)	(-1.64)	(2.66)
L_{NRC}	7.77	6.83	9.24	10.86	12.37	4.75	4.49	9.44
t	(1.09)	(1.01)	(1.48)	(1.66)	(1.88)	(2.34)	(2.63)	(1.45)
t_{boot}	(1.50)	(1.41)	(1.96)	(2.26)	(2.56)	(1.92)	(2.18)	(2.09)
Nobs	96	96	96	96	96	96	96	96
$R^2\%$	2.99	1.92	4.05	5.76	9.23	3.90	5.20	4.93
Panel B: K = 2Q								
L_0	11.43	10.28	7.84	8.85	5.07	-5.63	-4.54	8.61
t	(2.41)	(2.14)	(1.68)	(1.90)	(1.39)	(-2.72)	(-2.63)	(2.05)
t_{boot}	(3.06)	(2.68)	(2.11)	(2.43)	(1.34)	(-1.67)	(-1.69)	(2.72)
L_{NRC}	2.57	2.44	3.84	6.32	8.15	5.60	5.00	4.73
t	(0.53)	(0.49)	(0.97)	(1.41)	(1.94)	(2.96)	(3.07)	(1.10)
t_{boot}	(0.62)	(0.59)	(0.96)	(1.52)	(2.07)	(2.41)	(2.56)	(1.29)
Nobs	95	95	95	95	95	95	95	95
R^2	0.54	0.46	1.26	3.26	7.81	10.76	12.68	2.21
Panel C: K = 3Q								
L_0	11.81	10.36	8.04	9.12	5.09	-5.65	-4.52	8.77
t	(2.56)	(2.22)	(1.75)	(1.99)	(1.43)	(-2.99)	(-2.84)	(2.13)
t_{boot}	(3.01)	(2.60)	(2.10)	(2.43)	(1.31)	(-1.66)	(-1.67)	(2.66)
L_{NRC}	-1.46	-0.49	0.57	2.81	5.52	5.90	5.09	1.50
t	(-0.37)	(-0.12)	(0.17)	(0.74)	(1.73)	(3.30)	(3.36)	(0.43)
t_{boot}	(-0.37)	(-0.12)	(0.15)	(0.69)	(1.46)	(2.48)	(2.57)	(0.42)
Nobs	94	94	94	94	94	94	94	94
$R^2\%$	0.24	0.03	0.04	0.88	5.28	18.46	19.03	0.31
Panel D: K = 4Q								
L_0	11.85	10.31	7.93	9.06	4.98	-5.70	-4.54	8.69
t	(2.65)	(2.31)	(1.78)	(2.03)	(1.44)	(-3.30)	(-3.09)	(2.19)
t_{boot}	(2.91)	(2.51)	(2.02)	(2.34)	(1.25)	(-1.68)	(-1.68)	(2.55)
L_{NRC}	-2.66	-1.66	-0.44	1.61	4.08	5.39	4.68	0.30
t	(-0.74)	(-0.44)	(-0.14)	(0.46)	(1.44)	(3.40)	(3.46)	(0.09)
t_{boot}	(-0.65)	(-0.41)	(-0.11)	(0.39)	(1.05)	(2.19)	(2.32)	(0.08)
Nobs	93	93	93	93	93	93	93	93
$R^2\%$	1.07	0.40	0.03	0.39	3.79	20.83	21.68	0.02

This table presents the time-series predictive regression of five inflation beta-sorted portfolios as well as the estimates of the inflation risk premium on the lagged nominal-real covariance. The nominal-real covariance is measured by the time-varying relation between current inflation and future 1-quarter consumption growth, NRC_t . NRC_t is standardised to accommodate the interpretation with a mean equal to zero and a standard deviation equal to one. The left-hand side returns are compounded over the horizon of one, two, three, and four quarters. I skip the most recent quarter return (i.e. skip R_{t+1}) when compounding the left-hand side returns to avoid look-ahead bias in the NRC_t estimation. I report for each regression the estimated coefficient, with corresponding t -statistics based on Newey-West standard errors with optimal lags or based on standard errors that are derived from 1000 block-bootstrapped coefficient estimates and the adjusted R-squared (in percentage points). The full sample is from February 1995 to September 2019.

1.5 Origins of the time-varying inflation risk premium

I next examine the relative contribution of the price versus quantities of inflation risk in the five inflation beta-sorted portfolios to better understand the causes of the time-variation in the inflation risk premium.

1.5.1 Price and quantities of inflation risk

Boons et al. (2020) quantify the relative contribution of quantities versus the price of risk by estimating pooled regressions of returns of the inflation beta-sorted portfolios ($P = H, 2, \dots, L$ here) on inflation beta ($\beta_{\Pi,p,t}$), the nominal-real covariance (NRC_t), and an interaction term:

$$R_{p,t+3} = L_0 + L_{\beta_{\Pi}}\beta_{\Pi,p,t} + L_{NRC}NRC_t + L_{\beta_{\Pi} \times NRC}(\beta_{\Pi,p,t} \times NRC_t) + \varepsilon_{t+3}, \quad (1.9)$$

where the portfolios inflation beta ($\beta_{\Pi,p,t}$) are estimated by applying Equation (1.5) to the post-ranking returns of each portfolio.

Panel A of Table 1.6 presents the estimated coefficients (annualised) and t -statistics using both the time-clustered standard errors and bootstrapped standard errors. I focus on the 1-quarter ahead horizon (from $t + 2$ to $t + 3$). To aid interpretation, NRC_t is standardised in the time-series (as in Table 1.5) and $\beta_{\Pi,p,t}$ is demeaned in the pool to have a mean zero across portfolios and time.

I find that neither inflation beta nor the nominal-real covariance is a significant predictor of returns in the pool of inflation beta-sorted portfolios when the interaction term is not included in Column 1 (set $L_{\beta_{\Pi} \times NRC} = 0$). The R^2 is also low at 4.3%. I include the interaction term in Column 2 and observe a significant rise in the R^2 to almost 10.0%. The estimated coefficient on the interaction term is large and significant at 1.86 ($t_{boot} = 2.71$). In other words, when the nominal-real covariance is negative, expected returns decrease in inflation beta, but when the nominal-real covariance is positive, expected returns increase with beta. This result aligns with the large negative inflation risk premium in the subsample pre-2009 and the virtually zero inflation risk premium post-2009.

To further quantify the interaction effect between inflation beta and the nominal-real covariance, Panel B follows Boons et al. (2020) and presents predicted risk premia in four distinct cases when: (i) inflation beta is at plus or minus one (pooled) standard deviation from its mean and (ii) the nominal-real covariance is at plus or minus one (time-series) standard deviation from its mean. These predictions evaluate the joint significance of the coefficients, thereby alleviating concerns about the potential multicollinearity issue arising from the interaction term. I present both clustered and bootstrapped t -statistics.

Time-Varying Global Inflation Risk and the Zero Lower Bound

Table 1.6 Time-varying inflation risk premia in pooled regressions.

Panel A: coefficient estimates					
Model:	(1)	(2)	(3)	(4)	(5)
L_0	8.17	10.7	8.17	11.2	11.2
t	(1.93)	(2.67)	(1.93)	(2.80)	(2.81)
t_{boot}	(2.68)	(2.58)	(2.68)	(2.47)	(2.48)
L_{NRC}	10.1	7.11	10.1	6.57	6.48
t	(1.94)	(1.51)	(1.92)	(1.38)	(1.36)
t_{boot}	(1.82)	(1.30)	(1.80)	(1.20)	(1.18)
$L_{\beta_{\Pi}}$	0.521	-1.05	0.497	-1.33	-1.39
t	(0.41)	(-0.94)	(0.38)	(-1.22)	(-1.24)
t_{boot}	(0.61)	(-1.26)	(0.57)	(-1.63)	(-1.69)
$L_{\beta_{\Pi} \times NRC}$		1.86			
t		(2.44)			
t_{boot}		(2.71)			
$L_{\beta_{\Pi,p} \times NRC}$			1.98		2.89
t			(1.37)		(2.25)
t_{boot}			(2.32)		(3.38)
$L_{\beta_{\Pi,t} \times NRC}$				2.18	2.21
t				(2.52)	(2.53)
t_{boot}				(2.23)	(2.24)
Observations	480	480	480	480	480
Adjusted R ²	0.043	0.099	0.042	0.108	0.109
Panel B: predicted risk premia from model [2]					
Cases	High NRC_t	Low NRC_t			
High $\beta_{\Pi,p,t}$	20.38	-6.85			
t	(2.51)	(-0.84)			
t_{boot}	(2.23)	(-0.82)			
Low $\beta_{\Pi,p,t}$	14.75	14.57			
t	(2.33)	(1.69)			
t_{boot}	(1.75)	(2.41)			
Diff	5.63	-21.41			
t	(0.67)	(-1.88)			
t_{boot}	(0.54)	(-2.41)			

Panel A of this table present the estimated coefficient from pooled predictive regressions of annual returns of the five inflation beta-sorted portfolios on their lagged inflation beta, the nominal-real covariance, and an interaction term: $R_{p,t+3} = L_0 + L_{\beta_{\Pi}}\beta_{\Pi,p,t} + L_{NRC}NRC_t + L_{\beta_{\Pi} \times NRC}(\beta_{\Pi,p,t} \times NRC_t) + \varepsilon_{t+3}$. In model [1], I set $L_{\beta_{\Pi} \times NRC} = 0$, whereas Model [2] estimates all three coefficients freely. For Model [2], Panel B presents the predicted risk premia in four distinct cases. That is when $\beta_{\Pi,p,t}$ and NRC_t are at plus or minus one standard deviation from their respective means in the pool. Models [3] to [5] in Panel A analyse which components of inflation betas interact with the nominal-real covariance. Model [3] replace interaction term with the interaction between the nominal-real covariance and the portfolio-specific component of inflation betas, $\hat{\beta}_{\Pi,p} = T^{-1} \sum_{t=1}^T \beta_{\Pi,p,t}$. Model [4] replace interaction term with the interaction between the nominal-real covariance and the time-specific component of inflation betas, $\hat{\beta}_{\Pi,t} = 5^{-1} \sum_{p=1}^5 \beta_{\Pi,p,t}$. Model [5] includes both component-wise interaction terms. To accommodate interpretation, NRC_t is standardised in the time series to have a mean zero and standard deviation equal to one, whereas $\beta_{\Pi,p,t}$ is demeaned in the pool. I report for each regression the estimated coefficient, with corresponding t -statistics based on the time-clustered standard errors and bootstrapped standard errors and the adjusted R-squared (in decimal). The sample period is from February 1995 to September 2019.

When a portfolio has a high inflation beta and the nominal-real covariance is high, I find that the estimated risk premium is the largest at 20.38% ($t_{boot} = 2.51$). Intuitively,

1.5 Origins of the time-varying inflation risk premium

a portfolio of equity indices is risky when it responds favourably to pro-cyclical inflation shocks, exposing investors to consumption risk. When the nominal-real covariance and the inflation beta are both low, the predicted risk premium is also positive, but smaller at 14.57% ($t_{boot} = 2.41$), indicating that a portfolio is also risky when it reacts negatively to inflation shocks that contain bad news about future consumption growth. When the inflation beta is high and the nominal-real covariance is low, the predicted premia are negative and insignificant. Additionally, when the nominal-real covariance is high but the inflation beta is low, the predicted premium is positive and weakly significant.

The prediction results also show that the difference in expected returns between high and low inflation beta is positive when the nominal-real covariance is high and negative when the nominal-real covariance is low. This observation supports the notion that equity indices with low (high) returns when inflation rises are the most desirable to protect against adverse global market conditions if the nominal-real covariance is positive (negative). Moreover, the difference between the high-minus-low beta portfolio is larger in magnitude and significance when the nominal-real covariance is low. This is because the covariance between inflation and future consumption growth is stronger in absolute terms in the case of a low covariance (the standardised nominal-real covariance at one standard deviation below the mean equals -0.61, which is relative to 0.08 one standard deviation above the mean).

I conclude that when paired with nominal-real covariance, change in inflation beta, or the amount of inflation risk, contains important information about returns. In the spirit of Boons et al. (2020), I further decompose inflation beta into two parts: (i) a portfolio-specific component that captures cross-sectional variation in unconditional average inflation betas, $\hat{\beta}_{\Pi,p} = T^{-1} \sum_{t=1}^T \beta_{\Pi,p,t}$; and, (ii) a time-specific component that captures time-series variation in the cross-sectional average inflation beta, $\hat{\beta}_{\Pi,t} = 5^{-1} \sum_{p=1}^5 \beta_{\Pi,p,t}$.

As shown in Column 3, the interaction between the portfolio-specific component of inflation beta and the nominal-real covariance ($\beta_{\Pi,p} \times NRC_t$) provides independent information regarding returns in the pool. The coefficient estimate for the interaction term is 1.98 ($t_{boot} = 2.32$). The R^2 in Column 3 is only 4.2%, which implies that this specification does not account for variations in inflation beta that are pertinent to the pool of inflation risk premia.

The time-variance in the cross-sectional average inflation beta is the missing variation. Given the high R^2 of 10.8% in this specification, Column 4 demonstrates that the interaction between the time-specific components of inflation betas and the nominal-real covariance ($\beta_{\Pi,t} \times NRC_t$) contains important information regarding returns. The coefficient estimate is 2.18 ($t_{boot} = 2.23$), which translates to a significant increase of 11.10% in the difference in expected return between periods of low nominal-real covariance (i.e., the nominal-real

covariance is one standard deviation below its mean) and average nominal-real covariance, when the cross-sectional average inflation beta decreases by one standard deviation ($11.10\% = L_{\beta_{\Pi,t} \times NRC} \times -\sigma_{\beta_{\Pi,t}} \times -\sigma_{NRC} = 2.18 \times -5.09 \times -1$). The reasoning for this finding is that when the cross-sectional average inflation beta is low, the average asset is particularly risky when the nominal-real covariance is negative (inflation is counter-cyclical).

I simultaneously incorporate the two components of inflation beta (interacted with NRC_t) in the last column of Panel A in Table 1.6. Similar to the model in Column 2, which incorporates the interaction term between the nominal-real covariance and the raw inflation betas, $\beta_{\Pi,p,t} \times NRC_t$, the R^2 equals 10.9%. This finding shows that the majority of the relevant variance in inflation betas for risk premia is captured jointly by the portfolio and time-specific components of inflation betas.

1.6 Theoretical discussion

In this section, I build on the model by Boons et al. (2020) (hereafter BDDS2020) where I add the shadow rate to the exogenous process of the nominal-real covariance. The purpose is to provide economic intuition to the sign-switching process of the nominal-real covariance and to motivate its empirical relation with the shadow rate. Appendix A.4 contains detailed derivation. Here, I show analytically that the key model results in BDDS2020 remain valid with the addition of the shadow rate. To rationalise my empirical findings on global inflation risk premium, I cite and discuss the key equations for the implied inflation risk premium in BDDS2020.

1.6.1 Exogenous processes and stochastic discount factor

As the main point of departure from the framework of BDDS2020, I assume that, in addition to the simple mean-reverting AR(1) process, the nominal-real covariance can experience a sign switch due to the change in sign in the shadow rate. Specifically, consider the theoretical counterpart of the empirical process in Equation (1.4) for the nominal-real covariance (φ_t) as⁷:

$$\varphi_{t+1} = \varphi_{t+1}^a + \varphi_{t+1}^b, \quad (1.10a)$$

$$\varphi_{t+1}^a = \varphi_0^a + v(\varphi_t^a - \varphi_0^a) + \sigma_w w_{t+1}, \quad w_t \sim iid \quad \mathcal{N}(0,1), \quad (1.10b)$$

$$\varphi_{t+1}^b = \varphi_0^b + v(\varphi_t^b - \varphi_0^b) + b(s_t - \bar{s}), \quad (1.10c)$$

⁷Detailed derivation in Appendix A.4.1.

where the shadow rate s_t is assumed to be an exogenous state variable determined by the stance of monetary policy with constant volatility σ_s , and the term $\bar{s}$ is the steady state of the shadow rate. The purpose of the shadow rate inclusion is to rationalise my empirical findings and provide economic intuition. Thus, I adopt this partial equilibrium set-up, where I abstract from building a model of shadow rate determination. The process for the nominal-real covariance (φ_t) is decomposed into two parts: (i) φ_{t+1}^a follows the simple mean-reverting process as given in Equation (1.10b), (ii) and φ_{t+1}^b governs the time-varying intercept through the shadow rate, s_t , which can change sign over time as given in Equation (1.10c). Thus, the complete process for the nominal-real covariance is given by

$$\varphi_{t+1} = \varphi_0 + b(s_t - \bar{s}) + v(\varphi_t - \varphi_0) + \sigma_w w_{t+1}, \quad w_t \sim iid \quad \mathcal{N}(0, 1). \quad (1.11a)$$

Then, the exogenous processes for real consumption growth (Δc_{t+1}), inflation (π_{t+1}), and real dividend growth for asset i ($\Delta d_{i,t+1}$) are assumed to be consistent with the BDDS2020 model. The nominal-real covariance (φ_{t+1}) follows the process discussed above.

$$\pi_{t+1} = \mu_\pi + \rho_\pi(\pi_t - \mu_\pi) + \xi_\pi u_t + \phi_\pi u_{t+1}, \quad (1.12a)$$

$$\Delta c_{t+1} = \mu_c + \rho_c(\pi_t - \mu_\pi) + \xi_c \varphi_{t-1} u_t + \sigma_c \eta_{t+1}, \quad (1.12b)$$

$$\varphi_{t+1} = \varphi_0 + b(s_t - \bar{s}) + v(\varphi_t - \varphi_0) + \sigma_w w_{t+1}, \quad (1.12c)$$

$$\Delta d_{i,t+1} = \mu_i + \rho_i(\pi_t - \mu_\pi) + \xi_i \varphi_{t-1} u_t + \sigma_i \eta_{t+1}, \quad (1.12d)$$

$$u_t, \quad \eta_t, \quad w_t \sim iid \quad \mathcal{N}(0, 1). \quad (1.12e)$$

Inflation in Equation (1.12a) is an ARMA(1,1)-process with innovation $u_{\Pi,t+1} \equiv \phi_\pi u_{t+1}$. Inflation and inflation shocks affect the real economy via expected consumption growth in Equation (1.12b). Inflation π_t predicts consumption growth unconditionally and in a time-invariant way with sign and magnitude determined by ρ_c . In contrast, the inflation shock u_t predicts consumption growth in a time-varying manner, where the sign and magnitude of the predictability are given by $\xi_c \varphi_{t-1}$. Dividends in Equation (1.12d) are subject to the same risks as consumption but with potentially different exposures. The shocks u_{t+1} and η_{t+1} are standard normal.

The representative agent preferences are characterised by the Epstein-Zin recursive utility, which yields the log stochastic discount factor (SDF)

$$m_{t+1} = \theta \log \delta - \frac{\theta}{\psi} \Delta c_{t+1} - (1 - \theta) r_{c,t+1}, \quad (1.13)$$

where $r_{c,t+1}$ is the log return on the wealth portfolio, that is, the claim on aggregate consumption; $\delta \in (0, 1)$ is the discount rate; ψ is the elasticity of intertemporal substitution (EIS); and $\theta = \frac{1-\gamma}{1-\frac{1}{\psi}}$ with $\gamma > 0$ the coefficient of relative risk aversion. The SDF depends on both consumption growth as well as the return on wealth.

1.6.2 The nominal-real covariance

Consistent with BDDS2020, the nominal-real covariance, ϕ_t , plays a dual role in the model. It determines (i) the time-variation in the predictability of consumption with inflation and (ii) the stochastic volatility of expected consumption growth ⁸.

To see that the nominal-real covariance determines the time-variation in the predictability of consumption, one can run in the model the same two-stage procedure that this paper runs in the data in Equation (1.2) and Equation (1.3): a regression of consumption growth on lagged inflation in an expanding window fashion. Since the addition of the shadow rate does not directly enter the process of consumption growth and inflation, the model-implied coefficient on inflation remains the same as Equation (19) of BDDS2020:

$$b_t^K = \frac{Cov_t(\sum_{j=1}^K \Delta c_{t+1+j}, \pi_{t+1})}{Var_t(\pi_{t+1})} = h_K + \frac{\xi_c}{\phi_\pi} \phi_t, \quad (1.14)$$

where h_K is a constant that depends on the prediction horizon K and parameters of the inflation process. If $\xi_c \neq 0$, Equation (1.14) shows that inflation predicts cumulative consumption growth in a time-varying manner determined by ϕ_t . Equation (1.14) also illustrates that ϕ_t is a linear transformation of the variable $\hat{b}_t^{1Q}$ (also denoted as NRC_t), which I use in the data to measure the nominal-real covariance in Equation (1.2).

1.6.3 The price of inflation risk

To understand the asset pricing implications of the model, BDDS2020 specify innovations in the SDF by using a decomposition similar to Campbell et al. (2018).⁹ Factoring in the inclusion of s_t in the exogenous process, Appendix A.4.6 illustrate that the shock η_{t+1} , $u_{\Pi,t+1}$, and w_{t+1} remain driving separate news component of the SDF. Furthermore, the price of inflation risk $\lambda_{u,t}$ is, by definition, the compensation that the representative agent

⁸The nominal-real covariance also plays the role of stochastic volatility of expected consumption growth. Indeed, the model has stochastic volatility for neither inflation nor unexpected consumption growth, but it does have stochastic volatility for expected consumption growth through the term $\xi_c \phi_{t-1} u_t$.

⁹News to the SDF is captured by a function of news to different components: (i) news to contemporaneous consumption growth, (ii) news about the future expected path of consumption, (iii) and news about risk. Appendix A.4.5 contains detailed decomposition.

requires to hold one unit of inflation risk, $u_{\Pi,t+1}$. Therefore, the price of the inflation risk, $\lambda_{u,t}$, follows the Equation (23) of BDDS2020:

$$\lambda_{u,t} u_{\Pi,t+1} = \kappa_1 \left(1 - \frac{1}{\psi}\right) N_{PATH,t+1} \quad (1.15a)$$

$$= \kappa_1 \left(1 - \frac{1}{\psi}\right) \left(\frac{\rho_c \phi_\pi}{1 - \rho_\pi \kappa_1} + \frac{\rho_c \kappa_1 \xi_\pi}{1 - \rho_\pi \kappa_1} + \xi_c \varphi_t \right) \frac{u_{\Pi,t+1}}{\phi_\pi}, \quad (1.15b)$$

where $N_{PATH,t+1}$ is news about the future expected path of consumption and κ_1 is an approximation constant generally close to one. Equation (1.15b) provides the economic interpretation that inflation risk is priced because inflation shocks provide news about the expected future path of consumption growth. The first two terms inside the parenthesis arise through the term $\rho_c(\pi_t - \mu_\pi)$ in Equation (1.12b) and reflect the unconditional (non-time-varying) effect of the inflation on consumption.

The third term inside the parenthesis provides an explanation for why the price of inflation risk moves over time together with the nominal-real covariance. When $\varphi_t > 0$, the representative agent requires positive compensation for bearing inflation risk because positive inflation shocks contain good news about future consumption growth. On the other hand, if $\varphi_t < 0$, the representative agent is willing to accept lower expected returns to hold inflation risk because inflation shocks come with bad news about future consumption growth, making inflation a good consumption and marginal utility hedge.

1.6.4 The quantity of inflation risk and inflation betas

The quantity of inflation risk of asset i is given by its inflation beta. The inflation beta, $\beta_{\Pi,i,t}$, is defined as the coefficient in a regression of returns, $r_{i,t+1}$, on inflation shocks, $u_{\Pi,t+1}$. To derive the model-implied inflation beta, news to returns for any asset i is decomposed in a manner similar to the SDF. Then, the BDDS2020 model shows that inflation shocks only affect the expected paths of dividend and discount rate, but not their higher moments. In Appendix A.4.7, I show that, with the additional shadow rate term, it remains true that only news to the path of either dividends or discount rates contributes to inflation beta. For the

purpose of discussion, recall BDDS2020's Equation (26) directly,

$$\beta_{\Pi,i,t} = \frac{Cov_t(u_{\Pi,t+1}, r_{i,t+1})}{Var_t(u_{t+1})} \quad (1.16a)$$

$$= \kappa_{i,1} Cov_t(u_{\Pi,t+1}, N_{m,t+1}^i) + \kappa_{i,1} Cov_t(u_{\Pi,t+1}, N_{PATH,t+1}^i) \quad (1.16b)$$

$$= -\kappa_{i,1} \underbrace{\frac{\phi_\pi}{\psi} \left(\frac{\rho_c(\kappa_{i,1}\xi_\pi + \phi_\pi)}{1 - \kappa_{i,1}\rho_\pi} + \xi_c\varphi_t \right)}_{Cov_t(u_{\Pi,t+1}, N_{m,t+1}^i)} + \kappa_{i,1} \underbrace{\phi_\pi \left(\frac{\rho_i(\kappa_{i,1}\xi_\pi + \phi_\pi)}{1 - \kappa_{i,1}\rho_\pi} + \xi_i\varphi_t \right)}_{Cov_t(u_{\Pi,t+1}, N_{PATH,t+1}^i)}. \quad (1.16c)$$

Intuitively, when news to the path of either discount rate ($N_{m,t+1}^i$) or dividends ($N_{PATH,t+1}^i$) covary more with inflation shocks, the price of asset i is more exposed to inflation and the quantity of inflation risk increases. More importantly, the model implied inflation beta in Equation (1.16c) corresponds to the empirical estimation of the inflation beta in Equation (1.5), where the time-varying inflation beta is modelled to be linear in nominal-real covariance. Indeed, in Equation (1.16c), all the time variation in $\beta_{\Pi,i,t}$ comes from the nominal-real covariance, φ_t .

1.6.5 Risk premia of inflation beta-sorted portfolios

To derive the model-implied inflation risk premium from the cross-section of equity returns, I follow the BDDS2020 method and denote two assets that represent the High (H) and Low (L) inflation beta portfolios from the previous empirical analysis. The High-minus-Low inflation beta, $\beta_{\Pi,HL,t}$, is simply the difference $\beta_{\Pi,H,t} - \beta_{\Pi,L,t}$, because betas are liner in returns. As shown in Equation (30) in BDDS2020, if $\kappa_{H,1} \approx \kappa_{L,1} \approx 1$, a good approximation for $\beta_{\Pi,HL,t}$ is¹⁰

$$\beta_{\Pi,HL,t} = Cov_t(u_{\Pi,t+1}, N_{PATH,t+1}^H) - Cov_t(u_{\Pi,t+1}, N_{PATH,t+1}^L) \quad (1.17a)$$

$$= \frac{(\rho_H - \rho_L)(\xi_\pi + \phi_\pi)}{1 - \rho_\pi} + (\xi_H - \xi_L)\varphi_t \quad (1.17b)$$

with the associated inflation risk premium

$$\lambda_{u,t}\beta_{\Pi,HL,t} = \lambda_{u,t}(\beta_{\Pi,H,t} - \beta_{\Pi,L,t}). \quad (1.18)$$

¹⁰The High-minus-Low inflation beta is determined by how differently inflation shocks covary with news to the expected path of dividends for asset H versus asset L ($\xi_H - \xi_L$). The assumption that $\kappa_{H,1} \approx \kappa_{L,1} \approx 1$ makes the discount-rate components $\kappa_{H,1}Cov_t(u_{\Pi,t+1}, N_{m,t+1}^i)$ and $\kappa_{L,1}Cov_t(u_{\Pi,t+1}, N_{m,t+1}^i)$ of $\beta_{\Pi,H,t}$ and $\beta_{\Pi,L,t}$ identical, so they cancel out when taking the difference.

Thus, price of inflation risk ($\lambda_{u,t}$ in Equation (1.15b)) and the quantity of inflation risk ($\beta_{\Pi,i,t}$ in Equation (1.16c)) are each linear functions of the nominal-real covariance; and the inflation risk premium ($\lambda_{u,t}\beta_{\Pi,i,t}$) is quadratic in φ_t for asset i . This model takeaway rationalises the empirical exercise in Equation (1.9), where I regress the returns to inflation beta-sorted portfolios on the inflation beta, the nominal-real covariance, and their interaction term. In other words, the regressor inflation beta measures the quantities of risk, the nominal-real covariance measures the price of risk, and the interaction term stands for the inflation risk premium. Thus, this model motivates the empirical findings in Table 1.6 that variation in inflation beta (i.e. the quantity of inflation risk) contains important information about returns when combined with the nominal-real covariance (i.e. the price of inflation risk).

The model takeaway also helps to account for the time-varying excess returns to the High-minus-Low inflation portfolio in Table 1.4 and 1.5. Empirically, the portfolio beta $\beta_{\Pi,HL,t}$ is positive by construction. In turn, Equation (1.18) shows that the sign of inflation risk premia is only determined by the price of risk ($\lambda_{u,t}$), which is linear in nominal-real covariance. Before 2009, the nominal-real covariance is negative, and so is the $\lambda_{u,t}$. Thus, the returns of the High-minus-Low inflation portfolio comove positively ($\beta_{\Pi,HL,t} > 0$) with inflation shocks that contain bad news for future growth. The portfolio has a high payoff in bad states and a low payoff in good states, and the representative agent is willing to accept a negative premium for hedging purposes. When the nominal-real covariance entered the positive domain during the ZLB period, $\lambda_{u,t}$ is also approaching the positive range. Therefore, the returns of the High-minus-Low inflation portfolio comove positively ($\beta_{\Pi,HL,t} > 0$) with inflation shocks that contain good news. Its payoff is low in bad times and high in good times, exacerbating consumption risk and indicating an increased inflation risk premium.

1.7 Conclusion

This paper shows a time-varying inflation risk premium in the cross-section of the international equity market. This time variation is closely related to the change in the cyclical property of global inflation. In providing empirical evidence, this paper further documents a global phenomenon that inflation predicts real consumption growth in a time-varying way. In turn, this paper also studies the crucial driver of this time variation: the expected duration of the zero lower bound.

Beyond the US, I find international evidence that a global version of the nominal-real covariance is also strongly time-varying. To understand what is driving the time variation, I formally test the role of the expected duration of the ZLB in the determination of inflation cyclical property. My findings align with the proposed mechanism that as the changing

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expected duration of the zero lower bound varies the feasibility of the traditional stabilisation policy and the dominating shocks in the economy, the cyclical properties of inflation fluctuate correspondingly. In particular, the nominal-real covariance increases in the expected duration of the zero lower bound.

The main empirical asset pricing finding is that the inflation risk premium increases by a large and significant 4.8% for a standard deviation increase in the nominal-real covariance. Given an unconditional inflation risk premium of -5.5%, this result implies that the inflation risk premium can increase over time and change sign. The economic intuition is that when the nominal-real covariance is negative (e.g. during the 1970s), high inflation beta countries' equity indices are attractive as a hedge against bad states of nature and thus command relatively low expected returns. In contrast, when the nominal-real covariance turned positive (e.g. post-2009), a positive shock to inflation contains good news for future consumption. Thus, high inflation beta indices are risky (as they covary negatively with marginal utility), and the inflation risk premium shifts positively.

By decomposing the time-variation in the inflation risk premium into variation in the price and quantity of risk, I find that to understand the cross-section of global inflation risk premia requires knowledge not only of the relative magnitude of inflation betas across countries but also of the nominal-real covariance at each point in time. The reason is that both the price and quantity of inflation risk move over time together with the nominal-real covariance.

Chapter 2

Currency Returns and Interest Rate Surprises: It's All in the Shocks¹

2.1 Introduction

Since the global financial crisis, there has been renewed interest in understanding how monetary policy transmits across countries and drives the movement in the cross-section of asset returns worldwide. In a recent seminal contribution, Miranda-Agrippino and Rey (2020) present evidence that monetary policy in the US has significant spillovers to the rest of the world, generating strong co-movements of asset prices across countries. Nowhere is this topic more central than in the foreign exchange market, given the close link between currency markets and monetary policy in the models of exchange rate determination. However, the effect of monetary policy on the cross-section of currency return is not as well understood.

In this paper, we focus on the heterogeneous impact of the US monetary policy on currencies as follows. First, we purge monetary policy shocks from information shocks that may confound the effect on currencies. Second, we regress currency returns on the different structural shocks interacted with time-varying characteristics to obtain an “exposure index” (EXP) for each shock for every currency. Finally, we evaluate the economic magnitude of these effects by building long-short portfolios that sort currency on the different EXP indices and analyse their behaviour.

To distil the pure monetary policy effect on currencies, we carefully separate the monetary policy from other contemporaneous effects, particularly central bank information shocks. Jarociński and Karadi (2020) show that central bank announcements simultaneously convey

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information both about monetary policy and the central bank's assessment of the economic outlook. One can identify a monetary policy shock through a negative co-movement between the rate surprises and stock price changes. By contrast, a positive co-movement must reflect something in the central bank's announcement that is not news about monetary policy—a central bank information shock. The separation of the two components is crucial as a positive information shock leads to an improvement in economic activity, thus offsetting the tightening monetary policy. By analysing the co-movement of interest rates and stock prices in a narrow policy announcement window, we decompose interest rate innovations around the Federal Open Market Committee (FOMC) announcements into monetary policy and central bank information shocks.

Equipped with the two decomposed shocks, we now illustrate their distinct effect on exchange rates using simple univariate regression. We focus on exchange rates against the US dollar for the following 16 countries/regions: Australia, Brazil, Canada, Czech Republic, Euro Area, United Kingdom, Hungary, Japan, Mexico, Norway, New Zealand, Poland, Singapore, South Africa, Sweden, and Switzerland. For each currency, we regress the intraday spot rate return onto the monetary policy rate changes or decomposed shocks, respectively. Thus, the coefficients on the policy-related variables capture the heterogeneous response of each currency.²

The results of this simple exercise are summarised in Figure 2.1 and highlight two takeaways. First, separating the monetary policy from the offsetting information shock is crucial in analysing its effect on currencies. We find that the average response of currencies is negative to surprising US rate increases and tightening monetary policy shocks. This observation that foreign currencies tend to depreciate with contractionary policy is in line with the vast literature on the effect of monetary policy on exchange rate (e.g. Dornbusch, 1976; Kim et al., 2017; Rogers et al., 2018). In contrast to the policy shocks, there are heterogeneous responses among currencies to a positive information shock. The positive information shock about the macroeconomic outlook may command an offsetting effect on the accompanying rise in interest rate. Thus, we observe that foreign currencies can appreciate or depreciate with information shocks depending on which effect dominates. Overall, currencies tend to depreciate on tightening policy shocks but tend to appreciate when there are contemporaneous positive information shocks.³

²Figure B.2 reports the estimated country-specific average responses with 90 per cent confidence interval based on Newey-West standard errors.

³The currency responses on the two decomposed policy shocks may be consistent with the currency excess returns decomposition in Froot and Ramadorai (2005). A contractionary US monetary policy is likely associated with lower future consumption growth, which might lead to higher marginal utility, resulting in a rise in the risk premia. By decomposition, increased interest rates and future expected returns could be potential drivers behind the observed dollar appreciation with tightening policy shocks. In contrast, a positive information shock

Fig. 2.1 Country-specific responsiveness to shocks and characteristics.



This figure plots the country-specific responsiveness to monetary policy-related variables against the time-series average of currency interest rate differentials. The country's average response to monetary policy is estimated from the individual univariate regression $r_{i,t} = \theta_i \text{Shocks}_t + \varepsilon_{it}$, where i is the currency identifier, t is the date of the scheduled FOMC meeting, and r_{it} is the intraday currency spot return in the 30-minute window surrounding the FOMC press releases. Shocks_t is one of the structural shocks or innovations of interest: (1) policy rate changes, (2) purged policy shocks, and (3) central bank information shocks, respectively. A positive surprise/shock is tightening. The coefficient θ_i captures the policy exposure for each currency and is reported on the y-axis against their average interest rate differentials. The sample period is between 1996/01-07/2019.

The second takeaway is that fundamental variables like interest rate differentials help explain currencies' heterogeneous responses. To see this, Figure 2.1 sorts country-specific average responses against interest rate differentials. Despite the large difference in their interest rate level, the Japanese yen and Brazilian real react similarly to a 1% change in the US policy rate, where they both depreciate around 4%. This finding is unsurprising as the policy rate innovations do not disentangle the monetary policy shocks from the information shocks. The impact of monetary policy on currencies is thus underestimated because the

about the macroeconomic outlook may be related to higher future consumption growth and lower marginal utility, indicating a decrease in the risk premia. In the decomposition, reduced risk premia can lead to foreign currency appreciation. Thus, the behaviour of the foreign currency on the impact of positive information shocks could be affected by the offsetting forces from both a potential reduction in risk premia and a rise in interest rate, leading to the observed heterogeneous responses.

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positive information shocks have offsetting effects. In fact, a 1% tightening shock in the US monetary policy is associated with a large 8.2% depreciation in the Brazilian real. In contrast, the same movement in the central bank information shock is associated with around 4.6% appreciation in the Brazilian real. On the contrary, low interest rate currencies like the Japanese yen react at a smaller magnitude to policy and information shocks (-4.4% and -3.1%).

Motivated by the two above-mentioned stylised facts, this paper presents how to construct an “exposure index” that captures the cross-sectional and time-series differences in sensitivity to the different structural shocks among currencies. Specifically, our regressions use the cross-product of the policy-related variables with currency characteristics linked to policy sensitivity. This approach to incorporating time variation exposure follows the seminal work by Shanken (1990); and builds on the methods of Pástor and Stambaugh (2003) and Ozdagli and Velikov (2020). The characteristics underlying the EXP index capture the effects of various monetary policy transmission mechanisms, including interest rate differentials, trend CPI inflation differentials, the ratio of net foreign assets (NFA) over GDP, the beta of the currency to the US equity market, and a measure of “trade network centrality” that measures countries’ exposure to global shocks. We show that currencies tend to be more reactive to the US monetary policy if they are associated with net borrowers countries, peripheral in the global trade network, characterised by higher interest rates, and more exposed to equity risk.

Finally, we evaluate the economic magnitude of the monetary policy effects by building long-short portfolios that sort currency by the EXP indices and analyse their behaviour. We find that our EXP index is a strong predictor of returns in the cross-section of currencies. Specifically, currencies that are more sensitive to the US monetary policy (i.e. those that perform poorly when there is a tightening policy shock and those that perform well when there is a positive information shock) have significantly higher average returns than less sensitive currencies. A long-short trading strategy designed to exploit this effect achieves an annualised return of 5.18% with an annualised Sharpe ratio of 0.69 in an out-of-sample exercise from 2009 to 2019. While some of this return is captured by existing factor models, the strategy earns an annualised abnormal return of 3.47% even after controlling for the dollar and carry factors. Overall, the performance of the exposure strategy indicates that the effect of monetary policy is economically important even in the low interest rate environment post-2009. Thus, investors require compensation to hold the currencies that are more sensitive to the US monetary policy.

Related literature First, we contribute to the extensive literature on the effects of monetary policy on exchange rates. The well-known overshooting hypothesis of Dornbusch (1976)

predicts that a monetary tightening leads to an impact appreciation followed by a persistent depreciation of the domestic currency. However, empirical studies (e.g. Eichenbaum and Evans, 1995; Scholl and Uhlig, 2008) document evidence of “delayed overshooting puzzle” where domestic currency experiences a persistent (instead of immediate) appreciation. Kim et al. (2017) investigate different monetary policy regimes. They argue that the delayed overshooting puzzle is a phenomenon of the 1980s when the uncovered interest parity (UIP) failed, but it was severe enough to contaminate the entire sample period. During the post-Volcker era, exchange rates overshoot immediately on the impact of monetary policy shocks. In related works, Rogers et al. (2014) and Rogers et al. (2018) find that US monetary policy easing surprises lead to immediate dollar depreciation using intraday data. By taking a cross-section perspective, we contribute to this literature by not only examining the effect of monetary policy on the aggregate dollar exchange rate but also the heterogeneous responses of individual country pairs.

This paper also contributes to the literature that assesses the impact of high-frequency financial-market surprises around key monetary policy announcements on asset prices (Kuttner, 2001; Bernanke and Kuttner, 2005; Gürkaynak et al., 2005). This literature uses financial market responses to central bank announcements to identify monetary policy shocks and assess the causal impact of policy. However, Jarociński and Karadi (2020) illustrate that policy announcements come with central bank communication about the economic outlook, whose presence can bias the estimated effects of monetary policy. Precluding implausible prices and interest rates from a monetary shock using sign-restriction is also discussed in earlier works of Uhlig (2005) and Scholl and Uhlig (2008). In this paper, we combine high-frequency identification and sign restrictions to separate the monetary policy shock from the impact of the central bank information shocks. Our contribution is to investigate the purged monetary policy’s effect on currencies.

The third strand of related literature attempts to use indices based on time-varying firm characteristics to study the cross-section of stock returns. The pioneering work of Shanken (1990) allows asset betas to vary over time with the levels of the state variables using interaction terms. Similarly, Pástor and Stambaugh (2003) use stock-level characteristics to predict firms’ exposure to aggregate liquidity risk, Ozdagli and Velikov (2020) create an index of monetary policy exposure in the stock market, and these papers study the asset pricing implications of their respective index. In the context of the currency market, Dedola et al. (2017) find no systematic pattern in country responses (e.g. in asset prices and capital flows) to US monetary policy when grouping countries by characteristics. In contrast, by adopting a panel technique, we build on these papers to study the monetary policy risk

compensation in the cross-section of currency returns by relying on currency fundamentals linked to the monetary policy transmission channels of exchange rates.

2.2 Deconstructing interest rate surprises around monetary policy announcements

2.2.1 Identification of structural shocks

In line with the literature, we define here the monetary policy rate *surprises* as the interest rates changes in a narrow window around FOMC announcements (e.g., Kuttner, 2001; Gürkaynak et al., 2005; Nakamura and Steinsson, 2018). For example, Nakamura and Steinsson (2018) use a composite measure of policy surprises that incorporates changes in interest rates at different maturities spanning the first year of the term structure, which also captures the effects of “forward guidance.”

While it may be tempting to use these surprises as a proxy for monetary policy shocks, one should note that central bank announcements can simultaneously convey information about both monetary policy and the central bank’s assessment of the economic outlook. Jarociński and Karadi (2020) disentangle these two components from the high-frequency co-movement of stock prices to interest rate surprises and document their different effect on the economy. Their strategy is based on the recognition that a broad range of models suggests that a pure monetary policy tightening leads to lower stock market valuations because the present value of future dividends declines. One can then identify a monetary policy shock through a negative co-movement between the rate surprises and stock price changes. By contrast, a positive co-movement must reflect something in the central bank’s announcement that is not news about monetary policy—what the authors call a central bank information shock.

2.2.2 The econometric approach

High-frequency monetary policy surprise Our policy rate surprise uses an updated version of the data for “policy news shocks” in Nakamura and Steinsson (2018). Over the period from March 1995 to March 2014, we use the data available on Emi Nakamura’s website.⁴ We extend the original series to March 2019 following the same methodology, using the first principal component of the change in five interest rates.

⁴<https://eml.berkeley.edu/~enakamura/papers.html>.

2.2 Deconstructing interest rate surprises around monetary policy announcements

The first of these rate changes is the change in market expectations of the federal funds rate over the remainder of the month in which the FOMC meeting occurs. To construct this variable, we use data on the price of the federal funds futures for the month in question. The second variable used in constructing the policy rate surprise is the change in the expected federal funds rate at the time of the next scheduled FOMC meeting. The last three variables used are the change in the price of three eurodollar futures at the time of the FOMC announcements. We use eurodollar futures at horizons of one, two, and three quarters in the future. We collect the tick-by-tick transaction prices from TickWrite. The scale of the policy news shock is arbitrary. Consistent with Nakamura and Steinsson (2018), we rescale it such that its effect on the one-year nominal Treasury yield is equal to one. The unit of policy rate surprise is in percentage points.

Estimation of a VAR with policy rate surprise Similar to Jarociński and Karadi (2020), we separate monetary policy shocks from contemporaneous information shocks by analysing the high-frequency co-movement of our policy rate surprises measure and stock prices in the same 30-minute window around the policy announcement. Consider the structural vector autoregression (SVAR) with the following form:

$$A_0 m_t = \varepsilon_t, \quad (2.1)$$

where m_t is a 2×1 vector of two high-frequency policy surprise variables observed at time t , including the composite interest rate surprise and the S&P 500 stock market index;⁵ ε_t is an 2×1 vector of structural shocks; and A_0 is an invertible 2×2 matrix of parameters. The vector ε_t is Gaussian with mean zero and covariance matrix I_2 , the 2×2 identity matrix.

If we pre-multiply by A_0^{-1} , the reduced-form VAR is

$$m_t = u_t, \quad (2.2)$$

where $u_t = A_0^{-1} \varepsilon_t$. Thus, our baseline model is a VAR with a restriction that m_t does not depend on the lags of m_t and has zero mean.

High-frequency identification and sign restrictions We combine high-frequency identification and sign restrictions in order to identify the structural shocks of interest in our baseline VAR model. Empirically, our two policy surprise variables in vector m_t are both measured in a

⁵Our measure of the stock price surprise is the change in the S&P500 futures. We collect the tick-by-tick high-frequency futures data from TickWrite. The change is between 10 minutes before and 20 minutes after the announcement. The price change is in percentage.

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narrow window of 30 minutes around the announcement. Thus, high-frequency identification allows us to make the assumption that the announcement surprises m_t are affected only by the two shocks (the monetary policy shocks and information shocks) and not by other shocks.

Identifying restrictions in the VAR model.

variable	Monetary policy shocks	CB information shocks
<i>high frequency</i> rate changes	+	+
stock index	—	+

Restrictions on the contemporaneous responses of variables to shocks. + and — denote the respective sign restrictions.

We further use sign restriction, assuming that a pure monetary policy shock is associated with a positive rate change surprise and a drop in stock prices. In contrast, we assume that a central bank information shock is associated with a positive rate change surprise and an increase in stock prices. We identify the negative co-movement shocks as the monetary policy shocks and the positive co-movement shocks as the central bank information shocks. This second assumption separates two central bank announcement shocks. Their orthogonality is a standard requirement of structural shocks. The above framework model the surprises m_t as linear combinations of structural shocks.

2.3 Empirical approach

In this section, we present how to construct monetary policy exposure indices using the interaction of currency fundamentals with policy-related variables. We show that fundamentals help explain currencies' heterogeneous response to monetary policy and information shocks. We then discuss the construction of exposure portfolios.

2.3.1 Estimation of time-varying exposure

We allow for the responses of currencies to monetary policy and information shocks to vary both in the cross-section and in the time series. To do so, we model the shock exposures as a function of time-varying currency characteristics. Specifically, we run panel regressions of the characteristics that interacted with the shocks, in a similar spirit to what was done by Pástor and Stambaugh (2003) and Ozdagli and Velikov (2020) in another context. Our main

specification is

$$r_{it} = \sum_{k=1}^n \beta_k Z_{it}^k + \theta_i \text{Shocks}_t + \sum_{k=1}^n \gamma_k Z_{it}^k \times \text{Shocks}_t + \text{Country}_i + \text{Meeting}_t + \varepsilon_{it}, \quad (2.3)$$

where i is the currency identifier, t is the date of the scheduled FOMC meeting, r_{it} is the intraday currency spot return in the 30-minute window surrounding the FOMC press releases⁶, and Shocks_t is one of the structural shocks defined in the previous section.⁷ The variable Z_{it}^k is the k -th currency characteristic that can help capture the exposure of a currency to monetary policy. The variables Country_i and Meeting_t are country and meeting fixed effects. We do not include Shocks_t as a standalone regressor because it is subsumed by the meeting fixed effects.

Using the coefficient estimates $\hat{\theta}_i$ and $\hat{\gamma}_k$ from Equation (2.3), our currency exposure (EXP) indices can be estimated as

$$\text{EXP}_{it}^X = \hat{\theta}_i + \sum_{k=1}^n \hat{\gamma}_k \times Z_{it}^k, \quad (2.4)$$

where $X \in \{\text{MP}, \text{Info}, \text{Rate}\}$ refers to the monetary policy shocks, the information shocks, and the interest rates surprises. The resulting exposure indices capture both time-varying and cross-sectional differences in policy sensitivity. The indices are based on not only country-specific responses but also the contribution of each characteristic: the interaction terms model the time-varying component of the currency response as a function of currency characteristics, whereas the coefficient θ_i captures the average response of each country's spot rate changes to news/shocks.

2.3.2 Currency fundamentals

To estimate Equation 2.3 we consider five currency fundamentals that are linked to the monetary policy transmission mechanisms and policy sensitivity of currency spot rate: interest rate differentials, trend CPI inflation differentials, the ratio of net foreign assets (NFA) over GDP, the beta of the currency to the US equity market, and a measure of “trade network centrality” that measures countries' exposure to global shocks. We collect data

⁶We collect minute-by-minute spot exchange rate quotes from January 1996 to March 2019 from Refinitiv Tick History. We define exchange rates as units of US dollars per unit of foreign currency such that an increase in spot indicates an appreciation of the foreign currency. Our measure of the currency response to policy announcements is the percentage change in the spot rate between 10 minutes before and 20 minutes after the announcement.

⁷We also run an analogous regression using the rates innovations instead of the structural shocks to highlight the importance of the shocks decomposition.

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for currency characteristics from a number of sources. We provide here only a high-level description, but Appendix B.1 and B.2.2 contains more details.

The NFA/GDP ratio is an updated version of the Lane and Milesi-Ferretti (2018) dataset kindly provided by Gian Maria Milesi-Ferretti. For the Euro Area, we use the average of core euro countries: Austria, Belgium, Finland, France, Germany, and the Netherlands.

We splice the trade network centrality data of Richmond (2019), available on Robert Richmond's website until 2016⁸ with our updated data to 2019. Our updated data follows the original methodology and uses bilateral trade data from the International Monetary Fund's Direction of Trade Statistics. GDP data in US dollars are from the World Bank's World Development Indicators.

For each currency, we collect from Bloomberg a mixture of -IBOR rates, swap rates on interbank deposits, and implied yields to supply the daily interest rate data. Table B.1 lists the Bloomberg tickers. We interpolate the daily interest rate data to fill missing data and use a 20-day moving average to deal with outliers. For the euro area, we use the interest rate of Germany before 1999.

We estimate trend CPI inflation differentials by relying on a measure of trend inflation proposed by Cieslak and Povala (2015) and calculated for different countries using CPI indexes from the International Monetary Fund's IFS.

We construct the monthly US equity beta for each currency similarly to Lilley and Rinaldi (2020). To make sure that the conditional equity beta captures long-term currency characteristics, at the end of every month, we regress the daily log appreciation of each currency on the daily log return of the S&P 500 futures using rolling five-year windows. The futures data are sampled at the daily close of the stock market in New York.

Table 2.1 reports the time-series average of the five country characteristic variables along with the country-specific policy exposure. Figure B.3 visualises the relationship between these characteristic fundamentals and sensitivity by reporting the cross-sectional correlation between characteristics and responsiveness to shocks.

2.3.3 Construction to exposure indices sorted portfolios

We explore the asset pricing implications of monetary policy by performing a univariate sort on our policy exposure indices. We construct exposure indices to rate changes, pure policy shocks and central bank information shocks separately. At the end of every month, we sort currencies by appropriately lagged characteristics. For annual data (NFA and trade centrality) we create monthly series by keeping end-of-period data constant until a new observation

⁸<https://robertjrichmond.com/Data.html>.

2.3 Empirical approach

Table 2.1 Estimated country-specific responsiveness.

Country	Panel A: Average Responsiveness			Panel B: Average Characteristics				
	Rate Changes	MP Shocks	Info Shocks	NFA/GDP	Trade Centrality	Interest Rate Diff	Inflation Diff	Equity Beta
Australia	-7.18 (1.43)	-9.96 (2.12)	1.45 (3.02)	-0.54	0.36	1.80	0.41	0.15
New Zealand	-6.74 (1.52)	-9.40 (2.12)	1.63 (2.99)	-0.72	0.10	2.33	0.12	0.15
Norway	-6.19 (1.55)	-7.84 (2.29)	-1.12 (2.56)	0.80	0.26	0.87	-0.08	0.05
Hungary	-5.99 (1.27)	-8.11 (1.84)	0.53 (3.23)	-0.79	0.25	5.31	7.87	0.10
Sweden	-5.97 (1.36)	-8.05 (2.11)	0.24 (2.83)	-0.16	0.37	-0.30	-0.51	0.06
Poland	-5.68 (1.64)	-8.29 (2.25)	1.97 (2.39)	-0.48	0.35	4.93	3.87	0.12
Euro Area	-5.64 (1.24)	-7.11 (1.85)	-0.91 (2.43)	-0.13	0.77	-0.66	-0.57	0.00
South Africa	-5.63 (1.38)	-7.94 (1.57)	1.16 (1.93)	-0.12	0.21	6.52	4.58	0.23
Czech Republic	-5.25 (1.29)	-7.20 (1.89)	0.54 (2.52)	-0.26	0.31	1.11	2.62	0.06
Switzerland	-5.15 (1.22)	-5.88 (1.70)	-2.78 (2.11)	1.12	0.52	-1.83	-1.48	-0.07
Brazil	-4.86 (1.21)	-8.18 (1.50)	4.56 (1.75)	-0.32	0.24	12.92	4.98	0.25
United Kingdom	-4.63 (1.05)	-6.03 (1.64)	-0.26 (2.00)	-0.08	0.83	0.65	0.01	0.02
Canada	-4.23 (0.91)	-6.19 (1.20)	1.58 (1.60)	-0.07	0.61	0.02	-0.38	0.13
Japan	-4.21 (1.15)	-4.37 (1.56)	-3.14 (1.23)	0.43	0.67	-2.40	-2.29	-0.12
Mexico	-3.10 (0.89)	-5.71 (1.18)	3.84 (1.33)	-0.41	0.49	7.78	7.12	0.23
Singapore	-1.87 (0.64)	-2.59 (0.69)	0.22 (0.95)	1.98	0.93	-0.98	-0.91	0.05

This table reports the country's average response to different monetary policy-related variables and average country characteristics. Panel A reports the θ_i for each country estimated from the individual univariate regression $r_{i,t} = \theta_i \text{Shocks}_t + \varepsilon_{it}$, where i is the currency identifier, t is the date of the scheduled FOMC meeting, and r_{it} is the intraday currency spot return in the 30-minute window surrounding the FOMC press releases. Shocks_t is one of the structural shocks or innovations of interest: (1) policy rate changes, (2) purged policy shocks, and (3) central bank information shocks, respectively. A positive surprise/shock is tightening. We report Newey-West standard errors with optimal lags in parentheses. Panel B reports country-specific time-series averages for the five characteristic variables. The sample period is 01/1996-07/2019.

becomes available; moreover, we assume the end-of-period data is only available from the following March for trade centrality and April for NFA. We use a 3-month lag for all other characteristic variables. Then, for each one of the three measures of monetary policy surprise,

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we construct the currency-specific exposure index using the lagged characteristics and the corresponding sets of coefficients estimation results from Equation (2.3). In other words, our results are out-of-sample from January 2009 to July 2019.

At the end of each month, we re-balance the portfolio by forming five portfolios based on one of the three exposure indices and these portfolios are held for one month. Our benchmark portfolio results use quintile break points. The one-fifth of all available currencies in a given month that has the lowest exposure index value is allocated to the first portfolio (denoted “Low”), the next fifth is allocated to portfolio 2, and so on, and the one-fifth of all currencies with the highest exposure index value is allocated to the fifth portfolio (denoted “High”). Finally, we also analyse a portfolio that is long in the most sensitive currencies and short in the least sensitive currencies. Specifically, we take the Low-minus-High portfolio when the sorting signal is the exposure index to rate changes or policy shocks, because the most sensitive currencies are the ones that depreciate the most. On the contrary, we take the opposite High-minus-Low portfolio when we sort on the exposure index to positive information shock because the currencies that appreciate the most are the most sensitive ones.

We denote the above-mentioned long-short portfolios as per their sorting signal. The long-short exposure portfolios to rate changes, pure policy shocks, and central bank information shocks are denoted as Rate, MP, and Info portfolios, respectively. We also construct an aggregated monetary policy exposure portfolio, denoted Mix, by combining the MP and Info portfolios using an inverse volatility weighting scheme. Specifically, we compute the daily volatility of the MP and Info strategies using rolling five-year windows. The portfolio Mix is then constructed by allocating to the MP and Info portfolios with weights that are inversely proportional to their respective rolling volatility (standardising the weights so that they add up to one). An important feature of these long-short portfolios is that the long and short sides of the portfolio always have the same number of currencies.

In addition to the benchmark results with equal weights, we also report returns of rank portfolios, where weights are proportional to signal strength. Similar to the long-short portfolio construction, we sort the monetary policy rate surprise and shock exposure indices in descending order and the information shock exposure index in ascending order so that we allocate the most sensitive currencies to the largest rank. Similar to Asness et al. (2013), the weights are

$$w_{i,t}^{Rank} = c_t \left(\text{rank}(\text{EXP}_{it}^X) - \text{med}\{\text{rank}(\text{EXP}_{jt}^X)\} \right),$$

$$\text{where } c_t = \frac{2}{\sum \left| \text{rank}(\text{EXP}_{it}^X) - \text{med}\{\text{rank}(\text{EXP}_{jt}^X)\} \right|}. \quad (2.5)$$

The term c_t is a scaling factor such that the absolute sum of all portfolio weights equals two so that we are one dollar long and one dollar short as in the long-short portfolio case. The term $\text{med}\{\text{rank}(\text{EXP}_{jt}^X)\}$ indicates the median of the rank of the exposure index for all currencies in the cross-section at time t . Again, we take no position in the median exposure currency. Given this construction, the rank exposure portfolios are also long-short portfolios with no direct dollar exposure.

Finally, while we re-balance the exposure portfolios at a monthly frequency, we track the daily portfolio excess returns given that we have the daily currency excess returns available and this exercise is likely of interest to market participants. We obtain daily quotes on one-, three-, and six-month forward exchange rates from a number of sources because of data quality considerations. Our main source is JP Morgan; when data are missing, we rely on other two sources, Bloomberg and WMR via DataStream.⁹ Currency excess returns are the daily excess returns of a US-based investor holding foreign currency via IMM-dated forward contracts. Appendix B.2.1 provides details on the excess return computation.

2.4 Empirical results

2.4.1 Country-specific response to monetary policy

Table 2.2 reports estimates from the baseline panel regression in Equation (2.3). All variables are scaled by their standard deviation to ease the interpretation. Columns 1 to 3 report how different characteristics capture the exposure of exchange rates to policy rate changes, monetary policy and information shocks, respectively. Comparing the within adjusted R^2 between Column 1 and Columns 2-3, we can see that currency characteristics explain the currency sensitivity to the two decomposed shocks better than the case for rate changes. Notably, raw (i.e., not purged from information shocks) innovations in the interest rate do a weak job of analysing the monetary policy effects on currencies through characteristics.

The signs of the coefficients on the interaction terms with the currency characteristics also have nice economic intuition. For example, Column 2 presents the effect of the NFA/GDP ratio on responsiveness to policy tightening shocks. As tightening shocks tend to lead to foreign currency depreciation, a positive coefficient (0.169) means countries with higher NFA/GDP ratios (net lenders) are less responsive. Instead, positive information shocks

⁹While quoted exchange rates at the monthly frequency from WMR or Bloomberg seem to be more prevalent in recent academic studies due to their relatively long historical coverage, they seem to contain many apparent errors when sampled at the daily frequency. For example, the daily interest rate differentials that can be implied by forward and spot quotes contain many unreasonable outliers for a number of currency pairs. So we prefer to use quotes from JP Morgan, which do not present these issues.

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lead to foreign currency appreciation; thus, the negative coefficient (-0.152) in Column 3 also indicates that countries with higher NFA/GDP ratios (net lenders) are less reactive. In other words, the two decomposed shocks are both related to a rate increase but have different effects on the currency market, which the level of the NFA/GDP ratio can capture. Specifically, currencies of net debtor countries tend to be more responsive than those of net lender countries. This finding may be consistent with the notion that net debtor countries need to offer a premium to compensate investors willing to finance negative external imbalances as their currencies tend to depreciate in bad times (Della Corte et al., 2016).

Regarding trade centrality, central countries tend to be less exposed to monetary policy. As tightening shocks depreciate the foreign currency and lead to future contraction, a positive coefficient (0.231) in Column 2 indicates that central countries depreciate less under these circumstances. In Column 3, a negative coefficient (-0.244) indicates that central countries appreciate less or even depreciate when there is a good shock to the future US economic outlook. Thus, central countries seem to be a good hedge against adverse shocks and tend to respond less to monetary policy shocks. This observation may be related to the implication in Richmond (2019) that central countries are a good hedge against global consumption risk.

Lustig et al. (2011) argue that a US investor loads up on global risk by investing in high interest rate currencies and borrowing in low interest rate currencies. Aligning with this argument, we find that the coefficient on interest rate differential is significant and positive in Column 3, indicating a stronger appreciation of high-rate currencies to positive information shocks. However, its effect weakens in Column 2, meaning that interest rate differentials do not add incremental value in capturing the policy shock exposure of currency after controlling for other characteristics.

We include countries' inflation differentials in the regression because Engel et al. (2022) argue that the inflation differentials are a strong measure of monetary policy stance and a more persistent predictor of excess returns than the interest rate differential, especially post-2009. Thus, currency inflation differentials may pick up the policy sensitivity of a currency in a mechanism similar to the interest rate differential. In our pre-2009 regressions in Table 2.2 however, the estimated coefficients on inflation differentials are not statistically significant.

Currencies' equity beta is another crucial determinant of currency sensitivity. In related work, Lilley and Rinaldi (2020) document an increase in the conditional equity beta of currencies after 2009. They argue that while the spreads in interest rates across currencies were compressed following the global financial crisis, exchange rates needed to adjust to compensate investors through expected appreciation when risk premia increases. In other words, we expect high equity beta currencies to be more exposed to fluctuations in the future

economic outlook. Indeed, the coefficient of 0.138 ($t = 2.65$) in Column 3 indicates that if a currency's historical equity beta is high, then the currency tends to appreciate more with positive central bank information shocks.

Overall, US policy shocks have a larger impact on currencies of countries that are net borrowers, peripheral in the global trade network, characterised by higher interest rates, and on currencies with higher equity beta.

2.4.2 Returns to the exposure portfolios

In this section, we present our empirical results regarding the performance and characteristics of currency policy exposure strategies and portfolio exposure to other currency risk factors.

Benchmark results

Table 2.3 reports descriptive statistics for long-short currency portfolios constructed based on currency exposures to different shocks. We also present in Table 2.4 descriptive statistics on the cross-section of returns on portfolios sorted by exposure to different shocks. We present annualised average excess returns, Sharpe ratio, and the dollar and carry two-factor model alpha. Note that Table 2.4 reports results exclusively for the out-of-sample period which is from January 2009 to March 2019.

Table 2.3 shows that rate changes exposure portfolio (Rate) has an economically small average excess return, ranging from 1.48% to 1.86% per annum. For comparison, the popular carry trade strategy delivers average annualised excess returns of 12.13% during the pre-crisis period. To understand the poor performance of the Rate portfolio, in Table 2.4, we show that sorting currencies based on their exposure to the policy rate surprise does not lead to any clear pattern in the portfolio excess returns. This observation is in line with our earlier discussion that the impact of policy rate surprises may be underestimated because the coexisting monetary policy shocks and information shocks move the foreign currencies in opposite directions.

Policy exposure strategies accounting for decomposed shocks

We then report results for the exposure strategies when we purge the impact of central bank information shocks from the policy rate surprises. As shown in Table 2.3, during the pre-crisis period, the exposure portfolios to the two decomposed shocks (MP and Info) deliver economically significant and positive excess returns ranging between 6.18% and 9.37% per annum with annualised Sharpe ratio ranging between 0.87 and 0.97. The risk-adjusted

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Table 2.2 Monetary policy exposure estimation.

Model:	(1) Rate Changes	(2) MP Shocks	(3) Info Shocks
NFA/GDP $\times$ Rate Changes	0.174* (0.091)		
Trade Centrality $\times$ Rate Changes	0.074 (0.138)		
Interest Rate Diff $\times$ Rate Changes	0.030 (0.068)		
Inflation Diff $\times$ Rate Changes	-0.154 (0.135)		
Equity Beta $\times$ Rate Changes	-0.089 (0.068)		
NFA/GDP $\times$ MP Shocks		0.169** (0.083)	
Trade Centrality $\times$ MP Shocks		0.231* (0.136)	
Interest Rate Diff $\times$ MP Shocks		-0.040 (0.051)	
Inflation Diff $\times$ MP Shocks		-0.086 (0.124)	
Equity Beta $\times$ MP Shocks		-0.110 (0.092)	
NFA/GDP $\times$ Info Shocks			-0.152** (0.073)
Trade Centrality $\times$ Info Shocks			-0.244** (0.118)
Interest Rate Diff $\times$ Info Shocks			0.105* (0.062)
Inflation Diff $\times$ Info Shocks			-0.073 (0.093)
Equity Beta $\times$ Info Shocks			0.138*** (0.052)
Controls: Currency Characteristics	Yes	Yes	Yes
<i>Fixed-effects</i>			
Time	Yes	Yes	Yes
CountryNames	Yes	Yes	Yes
<i>Varying Slopes</i>			
Rate Changes (Country)	Yes		
MP Shocks (Country)		Yes	
Info Shocks (Country)			Yes
<i>Fit statistics</i>			
Observations	1,448	1,448	1,448
Adjusted R ²	0.665	0.686	0.659
Within Adjusted R ²	0.014	0.025	0.020

This table reports estimates from panel regressions estimated at the FOMC meeting-currency level. The regression follows $r_{it} = \sum_{k=1}^n \beta_k Z_{it}^k + \theta_i \text{Shocks}_t + \sum_{k=1}^n \gamma_k Z_{it}^k \times \text{Shocks}_t + \text{Country}_i + \text{Meeting}_t + \varepsilon_{it}$, where i is the currency identifier, t is the date of the scheduled FOMC meeting, r_{it} is the intraday currency spot return in the 30-minute window surrounding the FOMC press releases, and Shocks_t is one of the structural shocks or innovations of interest: policy rate changes in Model (1), policy shocks in Model (2), and information shocks in Model (3). The variable Z_{it}^k is the k -th currency characteristic that can help capture the exposure of a currency to monetary policy. The variables Country_i and Meeting_t are country and meeting fixed effects. All variables are scaled by their standard deviation to accommodate the interpretation. The sample period covers scheduled FOMC meetings between 1996/01 and 12/2008. Time standard errors are in parentheses.

performance is therefore similar in magnitude to that of a standard version of the carry trade, which has an annualised Sharpe ratio of 1.08.

Interestingly, the two decomposed shocks remain important in a compressed interest rate environment post-2009, where unexpected rate changes do not capture monetary policy surprises well. We show that decomposing the shocks delivers strategies with more appealing Sharpe ratios than those based on the rate changes exposure portfolio or carry trade. Indeed, the carry portfolio only delivers an annualised excess return of 3.40% with a Sharpe ratio of 0.35 in the post-crisis period. However, the exposure portfolio to the two decomposed shocks performs substantially better with a Sharpe ratio ranging between 0.57 to 0.69.

Table 2.4 focuses on the cross section of portfolios of currencies sorted by their policy exposure. Average returns are monotonically decreasing in EXP^{MP} , from 4.66% for the PL portfolio (with average $EXP^{MP} = -1.45$) to -0.85% for PH portfolio (with average $EXP^{MP} = -0.41$). This dispersion translates into a significant return for the Low-minus-High portfolio equal to 5.38% ($t = 2.64$). As tightening monetary policy shocks lead to foreign currency depreciation, a currency with a smaller (i.e., more negative) exposure index to policy shocks is more responsive. That is to say, our Low-minus-High portfolios go long the most sensitive currencies and short the least sensitive currencies. Thus, the positive average excess returns may be related to the compensation for investors to bear the policy exposure risk. This effect is similar in both magnitude and significance for alpha equal to 4.31% ($t = 3.08$). The excess return and alpha are slightly weaker in the rank-weighted portfolio than in the long-short portfolio, but their Sharpe ratios are both economically meaningful (0.52 and 0.70).

On the other hand, average returns are monotonically increasing in currency exposure to the positive information shocks from -1.49% for the PL portfolio (with average $EXP^{Info} = -0.14$) to 3.79% for the PH portfolio (with average $EXP^{Info} = 0.73$).¹⁰ In turn, the High-minus-Low portfolio, which loads up on exposure to information shocks, also yields a significant return equal to 5.13% ($t = 1.81$) and an alpha of 2.63 ($t = 2.05$). The average returns translate to a price of risk of around 0.60 as measured by the Sharpe ratio, well above the carry trade.

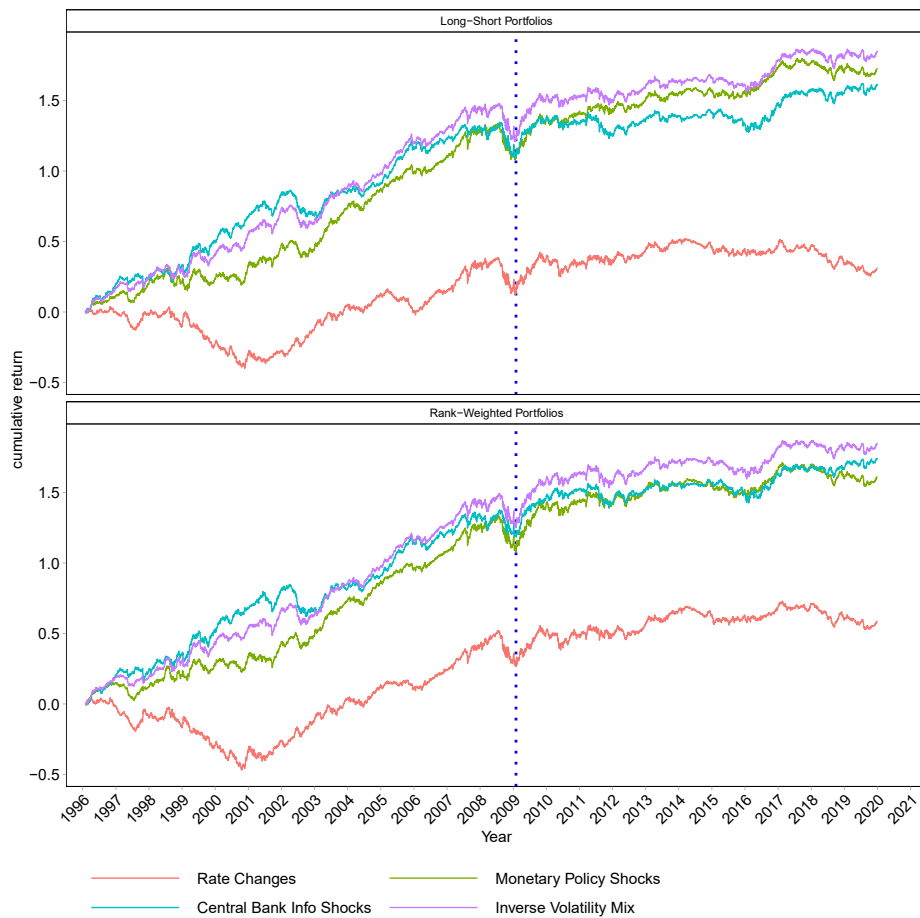
A natural question is how different are the exposure portfolios constructed from the decomposed shocks. We start by analysing the diversification benefits of the two portfolios by combining them. We report the performance of their aggregated exposure portfolio denoted as Mix. In the pre-crisis period, we can clearly observe the diversification benefit in the combined portfolio, where the Mix portfolio delivers a higher Sharpe ratio of 0.99.

¹⁰Positive information shocks lead to foreign currency appreciation; thus, currency with a higher exposure index to information shocks is more responsive.

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In the post-crisis period, Table 2.3 also shows that the Sharpe ratio of the Mix portfolio is on the higher side (0.69) compared to that of the two individual portfolios (0.70 and 0.57). Figure 2.2 reports the cumulative log excess returns to exposure portfolios. We can see that the MP and Info exposure portfolios present a clear divergence in the early 2000s. Also, the long-short MP and Info exposure portfolios have a relatively stable correlation (around 0.65) as shown in Table B.6. In addition, the two shocks generate distinct portfolio compositions as shown in Table B.8. Indeed, the MP and Info portfolios take the opposite position in several currencies (e.g. Mexican peso and Swedish krona).

Fig. 2.2 Cumulative log return to exposure-sorted portfolios.



This figure shows cumulative daily log excess returns accruing to exposure portfolios constructed by sorting currencies based on their exposure to the policy rate changes, monetary policy shocks and information shocks, respectively. We also report the results for an aggregate monetary policy exposure portfolio (Mix) using the inverse volatility weighted policy and information shock exposure strategies. The dashed line denotes the beginning of the out-of-sample period in January 2009. The portfolios are adjusted to have ex-post volatility of 10% per annum.

Table 2.3 Returns to currency monetary policy exposure strategies.

	02/1996-12/2008					01/2009-07/2019				
	Rate	MP	Info	Mix	Carry	Rate	MP	Info	Mix	Carry
Panel A: L/S Portfolios										
Mean	1.65	8.32	9.37	8.77	12.13	1.48	5.38	5.13	5.18	3.40
Median	2.18	12.66	13.16	12.11	13.63	0.56	5.20	6.46	5.50	3.52
Std. Dev	8.66	8.86	10.72	8.86	11.25	7.92	7.73	9.04	7.55	9.85
Sharpe Ratio	0.19	0.94	0.87	0.99	1.08	0.19	0.70	0.57	0.69	0.35
Skewness	0.06	-0.37	-0.32	-0.37	-0.12	0.03	-0.12	0.15	-0.04	-0.02
Kurtosis	3.46	3.56	3.17	3.57	3.46	2.90	2.98	3.50	3.31	3.46
AC1	0.08	0.14	0.17	0.19	0.19	-0.12	-0.12	-0.02	-0.05	-0.03
Max	8.79	7.38	9.67	8.47	11.22	5.38	5.88	9.28	6.64	7.87
Min	-7.34	-7.34	-8.06	-7.68	-8.36	-7.09	-6.07	-6.56	-6.10	-8.70
Pos	82	101	102	100	102	66	74	75	71	67
Neg	73	54	53	55	53	61	53	52	56	60
Panel B: Rank-Weighted Portfolios										
Mean	1.90	6.18	7.75	6.88		1.86	3.21	4.06	3.58	
Median	3.88	7.86	12.03	9.52		1.64	2.76	4.02	2.44	
Std. Dev	6.49	6.34	8.35	6.45		5.74	6.23	6.73	6.13	
Sharpe Ratio	0.29	0.97	0.93	1.07		0.32	0.52	0.60	0.58	
Skewness	-0.07	-0.30	-0.37	-0.29		-0.06	-0.11	0.10	-0.09	
Kurtosis	3.43	3.95	3.10	3.64		2.89	2.74	3.36	3.02	
AC1	0.08	0.16	0.17	0.20		-0.11	-0.08	0.01	-0.03	
Max	5.78	5.56	6.77	6.11		3.80	3.95	5.64	4.77	
Min	-6.40	-6.11	-7.23	-5.59		-4.72	-4.37	-5.70	-5.04	
Pos	85	99	99	104		70	68	75	68	
Neg	70	56	56	51		57	59	52	59	

This table reports descriptive statistics for currency portfolios based on exposures to different monetary policy shocks. We report results for the long-short portfolio where we sort currencies into five bins based on the exposure indices in Panel A, and the corresponding rank-weighted portfolio in Panel B. The exposure indices measure foreign currency's sensitivity to (1) policy rate changes (Rate), (2) pure monetary policy shocks (MP), and (3) central bank information shocks (Info). We also report results for an inverse volatility weighted aggregate portfolio of MP and Info, denoted Mix. We compare the monetary policy exposure portfolio with the carry risk factors. Excess returns are monthly and are defined such that positive numbers mean a positive return on holding the foreign currency. Mean returns, return volatility, and Sharpe ratio are annualised. Also shown are the return skewness, kurtosis, auto-regressive coefficient, the maximum and minimum monthly return, and the number of months with positive and negative returns. The sample period is between 07/1996-12/2008 for in-sample and 01/2009-07/2019 for out-of-sample.

Portfolio exposure to other currency risk factors

Next, we explore how the exposure strategies relate to the well-established common factors in the currency market: the dollar factor and the carry trade strategy. In this section, we will focus on the out-of-sample period from January 2009 to March 2019.

In Table 2.4, we also test the hypothesis that all five exposure sorted portfolio alphas are jointly equal to zero, using the test of Gibbons et al. (1989) and the carry and dollar two-factor

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model. The hypothesis is rejected at a 1 per cent significance level with t -statistics over three for both the cross-section of MP and Info portfolios. The hypothesis is also rejected at the 5 per cent level for the aggregate Mix portfolios. These results suggest that a two-factor model based on the dollar and carry factors cannot price the cross-section of exposure portfolios.

Then, we run regressions of long-short and rank portfolios returns on returns to carry and dollar risk factors. Estimated coefficients are shown in Table 2.5 with the Newey-West robust standard errors reported in parentheses. The slope coefficient estimates on the dollar and carry factors for the MP portfolios are positive and statistically significant. However, they are substantially different from unity (e.g. equal to 0.41 and 0.27 for the long-short portfolio). The returns to Info strategy load heavily on the carry factor with a beta of 0.72 for the long-short and 0.55 for the rank-weighted portfolio but are essentially uncorrelated with the dollar factor. This result is unsurprising as interest rate differentials contribute significantly to the information shocks exposure index. The resulting aggregate monetary policy strategies, Mix, have moderate exposure to both the dollar and carry factors. Furthermore, the alpha is statistically different from zero for MP, Info and Mix strategies and economically sizeable (ranges from 2.13% to 4.32% p.a.). Overall, the evidence suggests that monetary policy exposure portfolios are related but different from the dollar factor or the carry trades.

2.5 Conclusion

This paper studies the heterogeneous impact of the US monetary policy on currencies. First, to distil the pure monetary policy effect on currencies, we purge the monetary policy from the contemporaneous information shocks by analysing the co-movement of interest rates and stock prices in a narrow policy announcement window. We use simple univariate regression to illustrate the monetary policy and information shocks' offsetting effect on currencies. Currencies tend to depreciate on tightening policy shocks but tend to appreciate when there are contemporaneous positive information shocks. We also document that fundamental variables like interest rate differentials help explain currencies' heterogeneous responses in the cross-section.

Motivated by these two findings, we construct an "exposure index" that captures the cross-sectional and time-series difference in policy sensitivity among currencies. Our regressions use the interaction terms of the different structural shocks with currency characteristics linked to policy sensitivity. The resulting exposure indices show that currencies tend to be more reactive to the US monetary policy if they are associated with net borrowers countries, peripheral in the global trade network, characterised by higher interest rates, and more exposed to equity risk.

To evaluate the economic magnitude of the monetary policy effects, we build long-short portfolios that sort currency on the different EXP indices and analyse their behaviour. We find that currencies that are more sensitive to the US monetary policy announcement (i.e. those that react more negatively when there is a tightening policy shock and those that react more positively when there is a positive information shock) earn significantly higher average returns than less sensitive currencies. An aggregate policy exposure strategy designed to exploit this effect achieves an annualised return of 5.18% with an annualised Sharpe ratio of 0.69 from 2009 to 2019. While the returns moderately load on the dollar and carry factors, the strategy continues to generate a significant annualised abnormal return of 3.47%. The exposure strategy performance implies that the effect of monetary policy is economically important, both pre-2009 and post-2009, with different interest rate regimes. Thus, investors require compensation to hold the currencies that are more exposed to the US monetary policy.

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Table 2.4 Currency portfolio cross-section performance.

	PL	P2	P3	P4	PH	L/S	RW	GRS-t	GRS-pval
Panel A: Rate Changes Exposure Portfolios									
Mean EXP_t^{Rate}	-1.31	-1.12	-1.00	-0.85	-0.36	-0.95	-0.70		
Mean Return	1.84	0.65	0.10	-1.06	0.28	1.48	1.86		
t	(0.58)	(0.22)	(0.03)	(-0.42)	(0.15)	(0.69)	(1.20)		
Std. Dev	11.01	10.65	10.12	9.11	6.67	7.92	5.74		
Sharpe Ratio	0.17	0.06	0.01	-0.12	0.04	0.19	0.32		
α	1.25	0.24	-0.56	-1.03	0.14	1.02	1.33	1.07	0.38
t	(1.09)	(0.24)	(-0.63)	(-1.17)	(0.14)	(0.66)	(1.17)		
Panel B: Monetary Policy Shocks Exposure Portfolios									
Mean EXP_t^{MP}	-1.45	-1.22	-1.06	-0.88	-0.41	-1.04	-0.79		
Mean Return	4.66	0.17	-1.36	-0.39	-0.85	5.38	3.21		
t	(1.39)	(0.05)	(-0.53)	(-0.15)	(-0.44)	(2.64)	(1.74)		
Std. Dev	11.24	11.78	9.63	8.84	6.47	7.73	6.23		
Sharpe	0.41	0.01	-0.14	-0.04	-0.13	0.70	0.52		
α	3.64	-0.71	-1.54	-0.27	-0.81	4.31	2.14	3.75	0.00
t	(2.85)	(-0.74)	(-1.91)	(-0.29)	(-0.86)	(3.08)	(2.13)		
Panel C: Information Shocks Exposure Portfolios									
Mean EXP_t^{Info}	-0.14	0.26	0.43	0.60	0.73	0.88	0.69		
Mean Return	-1.49	-0.39	-1.74	2.24	3.79	5.13	4.06		
t	(-0.63)	(-0.16)	(-0.64)	(0.77)	(1.01)	(1.81)	(1.98)		
Std. Dev	7.22	8.43	10.16	10.81	11.76	9.04	6.73		
Sharpe Ratio	-0.21	-0.05	-0.17	0.21	0.32	0.57	0.60		
α	-0.85	-0.12	-2.00	1.51	1.95	2.63	2.15	3.06	0.01
t	(-0.81)	(-0.10)	(-2.20)	(1.33)	(2.09)	(2.05)	(2.18)		
Panel D: Mix Central Bank Exposure Portfolios									
Mean EXP_t^{Mix}	0.30	0.58	0.74	0.88	1.11	0.96	0.74		
Mean Return	-1.16	-0.37	-1.58	1.23	4.15	5.18	3.58		
t	(-0.56)	(-0.15)	(-0.62)	(0.39)	(1.20)	(2.28)	(1.90)		
Std. Dev	6.50	8.44	9.75	10.88	11.21	7.55	6.13		
Sharpe Ratio	-0.18	-0.04	-0.16	0.11	0.37	0.69	0.58		
α	-0.86	-0.18	-1.80	0.44	2.74	3.47	2.12	2.60	0.03
t	(-1.00)	(-0.22)	(-2.43)	(0.68)	(2.88)	(3.23)	(2.56)		

This table reports descriptive statistics for the set of sorted portfolios based on currencies' exposures to monetary policy rate changes, MP shocks, and Info shocks. We report the ex-ante average exposure indices. At the end of each month, we re-balance five portfolios based on one of the exposure indices, and these portfolios are held for one month. The one-fifth of all available currencies in a given month that has the lowest exposure index value is allocated to the first portfolio (denoted "PL"), the next fifth is allocated to portfolio 2, and so on, and the currencies with the largest exposure index value are allocated to the fifth portfolio (denoted "PH"). We report results for cross-sectional portfolio PL, P2, ..., PH, a long-short portfolio (L/s), and a rank portfolio (RW). Panel D reports the aggregate portfolios combining the MP and Info portfolios using inverse volatility weights. Note that the exposure index (EXP_t^{Mix}) and returns of the PL for the aggregate Mix portfolio combine the PH of the MP portfolio and the PL of the Info portfolio and so on so that the portfolios are combined along their level of sensitivity. Our long-short and rank portfolios are long in the most sensitive currencies and short in the least sensitive currencies. Mean returns, return volatility, Sharpe ratio, and alphas in excess of the dollar and carry factors are annualised. We report t -statistics based on Newey-West standard errors with optimal lags in parentheses. We also report Gibbons et al. (1989) (GRS) test statistics and p-value using a two-factor dollar and carry model for each set of sorted portfolios. The sample period is between 01/2009-07/2019.

Table 2.5 Exposure portfolio and FX risk factors.

	Rate	MP	Info	Mix	Rate	MP	Info	Mix
	Panal A: L/S Portfolios				Panal B: Rank-Weighted Portfolios			
Alpha	1.020 (1.535)	4.315*** (1.402)	2.632** (1.286)	3.469*** (1.075)	1.331 (1.142)	2.136** (0.998)	2.153** (0.901)	2.125*** (0.820)
Carry	0.079 (0.095)	0.268*** (0.093)	0.723*** (0.061)	0.475*** (0.067)	0.118* (0.066)	0.280*** (0.058)	0.551*** (0.036)	0.405*** (0.044)
Dol	0.523*** (0.057)	0.414*** (0.063)	0.091 (0.058)	0.265*** (0.048)	0.358*** (0.039)	0.335*** (0.035)	0.083* (0.044)	0.216*** (0.034)
Observations	123	123	123	123	123	123	123	123
Adjusted R ²	0.456	0.573	0.718	0.708	0.513	0.695	0.749	0.757

This table reports exposure regression results for long-short portfolios in Panel A and rank portfolios in Panel B. The dependent variables in Panel A and B are the excess return of an exposure portfolio based on different EXP indices. We consider exposure portfolios sorted on currencies' heterogeneous sensitivities to policy rate changes (Rate), purged policy shocks (MP), and information shocks (Info). Also reported are the results for an aggregated portfolio combining the MP and Info portfolios, denoted as Mix. As for factors in the regressions, we include excess returns to carry trades and dollar risk factors. Alphas are annualised and in per cent. We report Newey-West standard errors with optimal lags in parentheses. The sample period is between 01/2009-07/2019.

Chapter 3

Fundamental Momentum: The Impact of Trade Balance News on Currency Trends¹

3.1 Introduction

In recent years, foreign exchange (FX) markets have become an increasingly more popular laboratory for analysing momentum returns, i.e. the strategy that relies on past return continuation among winner and loser assets. FX markets are more liquid than stock markets, with an average daily trading volume of \$6.6 trillion as of April 2019 (BIS, 2019). Other characteristics of FX markets, such as low transaction costs, primarily sophisticated professional investors and no natural short-selling constraints, all raise the hurdle for generating profits from momentum strategies. Nevertheless, Menkhoff et al. (2012b) documented that the currency momentum strategy - long currencies that have yielded positive returns and short currencies that have yielded negative returns in the past - has been generating significant excess returns up to 10% per annum (p.a.) since 1976. Surprisingly, currency momentum is perhaps one of the least well-understood market anomalies. Burnside et al. (2011) shows that neither of the conventional risk models, risk factors derived from currency returns or vulnerability to rare disasters, presents any explanatory power towards currency momentum. Nonetheless, the possibility of using fundamentals news to rationalise the returns to currency momentum remains an area that has not yet been explored.

The main contribution of this paper is to understand currency momentum by studying how different currencies are related to fundamental information in the form of trade balance news. Recent events in the FX market remind us of the potential importance of US trade announcements on exchange rates. Following the US Department of Commerce's release of

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the US trade report on 10 August 2006, the dollar rallied strongly against currencies including the Japanese yen, euro, British pound, Swiss franc and Canadian dollar. The *Financial Times* on the same day attributed this significant climb of the US dollar to “a mass squaring of short positions betting on a fall on the dollar” after the no-worse-than-expected trade data reassure the traders (Johnson, 2006). Therefore it naturally calls for identification and documentation of the important role of trade balance news releases. Specifically, our motivation for focusing on trade figure announcement is twofold: (i) balance of trade is a crucial component of a nation’s current account, and it is comparable to the cashflow proxies (e.g. earnings) for a company, and (ii) announcements bring resolution to trade imbalance uncertainty and thus move currency excess returns (see e.g. Della Corte et al., 2016; Mueller et al., 2017).

Our empirical analysis shows that the overall currency market movement is larger on trade news announcements days than on non-announcement days. Indeed, the trade news announcement occurrence is a significant positive predictor of the time variation in the absolute dollar factor. To further measure the market participants’ reaction at the currency level, we compute the cumulative three-day abnormal returns for each currency around every trade news announcement in the spirit of Novy-Marx (2015). In turn, we form the macro fundamental currency momentum - trade news momentum - by longing the currencies that receive positive market reactions and shorting the currencies that receive negative market reactions.

We find a large Sharpe ratio to the trade news momentum of 0.54 per annum (p.a.). Importantly, trade news momentum is related to but different from the past price momentum documented in Menkhoff et al. (2012b) in terms of the spreads in their corresponding trading signal, portfolio return characteristics, return correlations and portfolio compositions. Trade news momentum is also different from the widespread carry trade in FX markets, providing appealing returns that are largely unrelated to carry trade returns.²

We continue our investigation of the trade news momentum by taking a time-series perspective. The time-series regressions suggest that the trade news momentum returns are positively but imperfectly correlated with the past price momentum returns. Furthermore, the alpha to the trade news momentum remains positive and significant after controlling for the dollar factor, carry trade and price momentum strategies. Interestingly, the trade news momentum commands strong explanatory power toward the past price momentum alpha. Further analysis of the cross-section of sorted portfolios indicates that investors expect high (low) returns on the past winner (loser) currencies in the price momentum because those currencies receive positive (adverse) market reactions following the trade news releases. This

²The carry trade is a popular trading strategy that borrows in currencies with low interest rates and invests in currencies with high interest rates.

finding suggests that the cross-section predictability of currency's past performance can be rationalised by the corresponding movements in fundamentals, captured by the cross-currency spread in market reactions to the trade news announcement.

To reconcile the novel finding, we investigate what drives the heterogeneity in currencies' exposure to trade news in connection with central bank interventions. We study whether the impact of trade news in cross-section excess return can be attributed to the costs to central banks undertaking more frequent interventions. The hypothesis is that movement in economic fundamentals (e.g. trade balance) will lead to a more potent trending mechanism in returns for currencies whose central banks choose to intervene heavily. The trend-follower should earn more profits from trade news momentum strategies constructed from currencies under heavy interventions.

Subsample analysis confirms the above predictions. We study two dimensions of central bank intervention: capital account controls and exchange rate regime choices. We show that subsamples of currencies with either heavy capital account controls or fixed exchange rates generate stronger trade news momentum than currencies under fewer interventions. These findings support the argument that currencies under interventions can afford less trade imbalance, and their excess return movement is more predictable. Thus, the profitability of trade news momentum can be reconciled with the costs to central banks.

3.2 Related literature

This section briefly discusses earlier literature on momentum in stocks and FX markets, studies looking at momentum in connection with fundamentals and the effect of central bank interventions.

The paper contributes to a large strand of literature towards understanding the high returns to price momentum strategy. The pioneering work by Jegadeesh and Titman (1993) first documented that simple momentum strategies in the US stock market generate high returns of about 12% p.a., which are difficult to explain by conventional asset pricing models. Unlike in stock markets, currency momentum studies generally analyse momentum in time series of the individual exchange rate (technical trading rules) instead of in the cross-section of currencies. In recent years, cross-section currency momentum strategies have attracted increasingly more attention. Okunev and White (2003) provide some evidence of cross-sectional momentum profits in the context of small cross-sections of eight currencies. The seminal work by Menkhoff et al. (2012b) provides a broad empirical investigation of currency momentum by analysing a universe of 48 currencies from 1976 to 2010. They find that simple currency

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momentum strategies generate average excess return up to 10% p.a., and the high returns can only be partially explained by transaction cost.

Surprisingly, despite the puzzling profitability of currency momentum, it is perhaps one of the least well-understood market anomalies. In a survey on currency momentum by Burnside et al. (2011), the authors show that none of the conventional risk models exhibits explanatory power towards currency momentum returns. Additionally, the authors provide results using factors derived from currency returns, including the dollar risk factor, carry trade factor in Lustig et al. (2011), and the global currency volatility factor in Menkhoff et al. (2012a). None of these currency factors explains the currency momentum returns either. The vulnerability to rare disasters and peso problems are also ruled out as potential explanations. Overall, the literature does not seem to have a generally accepted rationale for either momentum in general or currency momentum in particular.

This paper is closely related to studies examining links between momentum and fundamentals. Novy-Marx (2015) empirically shows that a fundamental momentum strategy that long stocks with positive earnings surprises and short stocks with negative earnings surprises can fully explain the performance of standard past price momentum. The author thus concludes that the cross-sectional predictability of stock past performance is only a signal of corresponding movements in fundamentals (earnings). In the FX markets, Dahlquist and Hasseltoft (2020) provide evidence that past macro fundamentals trends predict currency return. They find that a currency strategy that exploits the past macroeconomic trend can capture the returns to carry trade. Instead of economic trends, this paper is complementary to the literature in that we focus on finding the analogy of stock earnings momentum in the form of fundamental news.

In this paper, we concentrate on US trade data release, and our motivation is twofold. First, without arguing that trade balance is the only economic factor that matters, we want to highlight the critical role played by trade data in exchange rate determination (see Della Corte et al., 2016). Trade balance measures a nation's flow of its exports and imports of goods and services over a period, which by construction always equals the nation's net capital flow. Therefore, the trade balance is comparable to a company's cash flow proxies, such as earnings. In that sense, it would seem natural that trade-related news may help shed light on the strength of a country's balance sheet and thus helps our fundamental understanding of currency price dynamics.

Secondly, our paper relates to the vast literature on economic announcements bringing resolution to uncertainty as we mainly look at the occurrence of the announcement (i.e. the release dates) but not the sign of the announcement. In the exchange rate determination model by Gabaix and Maggiori (2015) (GM), financiers face constraints that limit their

ability to absorb the currency risk arising from globally imbalanced trade. Building on the GM model, Mueller et al. (2017) give a role to the uncertainty in the realisation of monetary policy in determining the demand and supply of currencies. They show that, on average, financiers require higher currency excess returns to compensate for the higher monetary policy uncertainty irrespective of the announcement results. In this paper, we argue that higher trade imbalance uncertainty exists before the announcement moves the exchange rate. Sorting on individual currencies' three-day cumulative returns around US trade data release, we let the data speak for the directions of exchange rate movements than let the sign of announcement decide. In a sense, we focus more on the mechanism that the resolution of uncertainty on trade data brings new information into the public domain and thus affects the currency prices.

Our rationalisation of the excess returns to trade news momentum is related to the literature on central bank intervention practices. Menkhoff and Taylor (2007) summarise that earlier works in this area mainly concern the influence of interventions on technical analysis profitability. The pioneering work by LeBaron (1999) shows that removing days when central bank activity is high dramatically reduces the exchange rate predictability. Similar results are from Szakmary and Mathur (1997). However, later papers, such as Neely (2002), reach different conclusions that interventions only happen after technical trading rules profited and thus do not influence its profit. At first sight, our findings that currencies under more frequent interventions generate stronger trade news momentum may appear odd to the early literature. However, these studies only focused on time-series trends and worked with just a few currencies, and our findings instead come from a much broader cross-section perspective.

Our findings may be more related to the recent study by Fratzscher et al. (2019), which examined FX intervention's effectiveness with a broad cross-sectional of currencies. Using daily data of sterilised interventions from 33 central banks, they empirically show that central banks typically lean against the wind. Moreover, FX interventions occur nearly four times more often on currencies with narrow band regimes than floating and broad band regimes. Regarding the FX regime objectives, they find that the main objective in floating regimes is moving exchange rates in the intended direction (e.g. to reverse an appreciation trend). On the contrary, the most relevant objective in narrow band regimes is stabilising exchange rates in a tight band (e.g. to reduce an appreciation trend rather than reverse it).

Building on Fratzscher et al. (2019), we attribute our findings of trade news predictability in cross-sectional currency excess return to the costs to those central banks who wish to intervene more. Instead of being profit-driven, central banks mostly counter prevailing market forces. However, one needs to account for the heterogeneity in the main objectives for central banks with different currency regimes. On the one hand, central banks intervene

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less often in floating regimes, and the main intervention goal is usually moving the exchange rate in the intended direction. Therefore, one would see fewer currency trends when there is news about trade imbalance (floating exchange rate can automatically adjust quickly). Thus, we observe a weaker performance of trade news momentum using a subsample of floaters.

On the other hand, central banks that are managing narrow exchange rate bands intervene more often with the primary goal of smoothing and stabilising. Thus, these central banks are more likely to smooth out or delay sudden exchange rate movements when there are fundamental economic shifts. Hence, banks with narrow band exchange rate regimes will likely generate non-random exchange rate movement (delay in adjustment) and thus suffer losses to trend followers, which rationalised the stronger trade news momentum.

3.3 Data and currency portfolios

In this section, we describe the data, sample construction, the computation of currency excess returns, and the construction of FX trading strategies.

3.3.1 Data and sample construction

The core analysis of the link between the trade news releases and currency returns requires daily data on the spot and forward exchange rates and the announcement dates of the US trade balance report. Our total sample consists of the following 29 countries: United Kingdom, Switzerland, Japan, Canada, Australia, New Zealand, Sweden, Norway, Denmark, Euro Area, Germany, Hong Kong, South Africa, Singapore, Czech Republic, Hungary, India, Indonesia, Malaysia, Mexico, Philippines, Poland, Saudi Arabia, South Korea, Taiwan, Thailand, Brazil, Russian Federation, Israel. The sample period is from March 1994 to December 2018.

To understand the heterogeneity in currencies' sensitivity to trade news, we also consider if a currency is pegged or subject to capital restriction. For the exchange rate regimes, we use the coarse classification codes provided by Ilzetzi et al. (2019). Details of the exchange rate regime classification are reported in Table C.1. The subsamples of countries with floating exchange rates comprise countries in regime 3 or 4, while the subsamples of countries with fixed exchange rates comprise countries in regime 1 or 2.

To identify countries with different levels of restrictions on cross-border capital transactions, we use the capital account openness index (denote as *kaopen*) of Chinn and Ito (2006). The subsamples of countries with a *kaopen* index greater than or equal to zero are categorised as having open capital accounts. The subsamples of countries with close capital accounts

are the countries' *kaopen* index to be smaller than zero. Table C.2 reports the number of observations a currency enters in different subsamples.

Trade Balance Announcement

Every month, the US Department of Commerce News release the report on US International Trade in Goods and Services via the US Census Bureau website. The report contains detailed information about the US monthly imports and exports of goods and services, the trade deficits or surpluses, as well as the balance of trade per trade partner country.

The exact dates for the US international trade report release are hand collected from the US Census Bureau website. It is worth noting that the monthly trade data release is formally scheduled and the schedule is available to the public. The trade news was often scheduled to be released during the third week each month in the 1990s, but this has been gradually changed to the first week each month nowadays. Also, the trade news usually has a 2-month lag; for example, the trade data for January 1994 is released in the 22 March 1994 report.

Exchange Rate Data

We obtain daily spot and 1-month forward exchange rates from Barclays Bank International (BBI) and Reuters via Datastream. We denote the spot and forward rates in logs as s and f , respectively.

We note that the effective size of the asset universe changes over time because data for some currencies become available later or when currencies cease to exist.³ Individual start and end dates for each currency are shown in Table C.2. After the euro's introduction in January 1999, the Deutsche mark rate is replaced by the euro for the rest of the period. As in Lustig et al. (2011) and many related studies, we remove data when we observe significant deviations from the covered interest rate parity (CIP) condition.⁴

3.3.2 Currency portfolio construction

Below we describe how we construct the relevant currency strategies from the spot and forward exchange rates and trade new announcements.

³The total sum of actual observations (currency-day combination) is 156,720 instead of the theoretical maximum of 187,311 (6459 days for 29 currencies).

⁴We filtered the data as follows: Malaysia from May 1998 to June 2005; Indonesia from December 1997 to July 1998, and from December 2000 to May 2007; Russia from December 2008 to January 2009; South Africa for August 1985, and from January 2002 to May 2005.

Currency Excess Returns

Monthly excess returns to a US investor for holding a foreign currency are given by

$$rx_{t+1}^k \equiv \Delta s + (i^k - i_t) = s_{t+1} - f_t, \quad (3.1)$$

where i^k denotes the one-month interest rate in country k , i without a superscript denotes the interest rate at home (the US here). s and f denote the log spot and one-month forward rate, respectively. Exchange rates are quoted as US dollars per one unit of foreign currency k such that an increase in s_t indicates an appreciation of the foreign currency. Δs denotes the log spot rate return. Akram et al. (2008) show empirically that covered interest rate parity (CIP) holds even at very short horizons. Thus, interest rate differentials ($i^k - i_t$) equal forward discounts $s_t - f_t$ in Equation (3.1).

We approximate daily currency excess returns by combining the daily log spot return and the forward discount divided by 21 days. Descriptive statistics for excess returns and forward discounts are reported in Table C.2.

Market reaction to trade news

We follow Novy-Marx (2015) and use cumulative three-day abnormal returns ($CAR3$) to measure the market participants' reaction regarding the trade news release. Specifically, we define the currency daily log abnormal returns ($rx_{k,t}^a$) as currency k 's excess returns net of the returns on dollar risk factor⁵ at time t , i.e. $rx_{k,t}^a = rx_{k,t} - rx_{DOL,t}$.

Then, we define $CAR3$ as the cumulative abnormal return earned by longing a foreign currency k and shorting one US dollar over the three-day window starting the day before a trade news release and ending at the end of the day following the news release. Suppose there is a trade news announcement on the day t , and the cumulative three-day abnormal return ($CAR3$) for country k at time t is given by

$$CAR3_{k,t} = rx_{k,t-1}^a + rx_{k,t}^a + rx_{k,t+1}^a. \quad (3.2)$$

Table C.3 shows descriptive statistics for the $CAR3$ for individual currency.

⁵As in Lustig et al. (2011), we constructed a portfolio that is the average of all available currencies in each month. We call this portfolio the dollar risk factor, DOL , as this portfolio represents the average return of a strategy that borrows money in the US and invests in all foreign money markets.

Trade news currency momentum

We discussed that the magnitude and sign of the cumulative three-day abnormal return for each currency could be informative about the market participants' reaction to the trade news release. Thus, at the end of the three-day window around each trade announcement, we compute the cumulative three-day abnormal return for each currency from day $t - 1$ to $t + 1$. Then, on the day $t + 2$, all currencies are allocated to five portfolios based on their $CAR3$ s and held until the $CAR3$ s for the next trade announcement become available. The one-fifth of all available currencies that have the lowest $CAR3$ around the trade news announcement is allocated to the first portfolio, the next fifth is allocated to portfolio two until the last one-fifth of all currencies that have the highest $CAR3$ around the trade news release are allocated to the fifth portfolio. The currencies within each portfolio are equally weighted.

Then, we construct an analogue strategy to the earning momentum factors in Novy-Marx (2012). Specifically, the trade news momentum portfolio involves a long position in the currencies that have the highest $CAR3$ (i.e. portfolio *High*) and a short position in the currencies that have the lowest $CAR3$ (i.e. portfolio *Low*). In other words, our trade news momentum is longing for the currencies that receive a positive market reaction following the trade news release and shorting the currencies that receive a negative market reaction. We denote the trade news momentum as $CARMOM$. Note that for the *High-minus-Low* portfolio to be dollar neutral, we make sure that these two portfolios always have the same number of currencies so that the dollar component cancels out when taking the difference.

Past price currency momentum

For comparison with the trade news momentum, we build the traditional momentum strategy in the spirit of Menkhoff et al. (2012b). At the end of each month, five portfolios are formed based on lagged cumulative excess returns over the previous 1-month and these portfolios are held for 1-month. The one-fifth of all available currencies that have the lowest cumulative returns during a given formation period are allocated to the first portfolio, and the next fifth is allocated to portfolio two until the last one-fifth of all currencies that have the highest cumulative excess returns are allocated to the last portfolio. The currencies within each portfolio are equally weighted.

Then, the traditional momentum portfolio is the portfolio that is long in the past winner currencies and short in the past loser currencies. We denote this long-short portfolio $PMOM$, past price momentum.

Carry trade

At the end of each month t , we also construct a carry strategy where we allocate currencies to five portfolios based on their daily forward discounts $s_t - f_t$ and these portfolios are held for 1-month. According to the CIP condition, sorting on the forward discount is equivalent to sorting on interest rate differentials. Again, the first portfolio contains currencies with the lowest interest rates, and portfolio 5 contains currencies with the highest interest rates.

The carry trade portfolio, denoted *CARRY*, borrowing money in the low-interest-rate countries and investing in the high-interest-rate countries is obtained by taking the difference between the high and low interest rate portfolios.

3.4 Empirical analysis

In this section, we present our main empirical results regarding the properties of the excess returns to trade news currency momentum and a comparison with the excess returns from the currency past price momentum and the carry trade strategies. We also present the time-series regressions results.

Announcement effects

We begin our empirical investigation by documenting how the mere occurrence of a trade news announcement affects the currency market activity. We build on Mueller et al. (2017) and regress the absolute excess returns of the dollar factor ($|DOL_t|$) on a trade news announcement dummy with some control variables. Our use of the absolute return aims to capture the summed magnitude of the currency market movement regardless of the direction of the news. The regression is given by

$$|DOL_t| = \alpha_0 + \alpha_1 \text{Announcement}_t + \alpha_2 |DOL_{t-1}| + \alpha_3 \text{EndofMonth}_t + e_t, \quad (3.3)$$

where Announcement_t is the dummy variable that takes the value of one on trade news announcement days and zeroes otherwise, $|DOL_{t-1}|$ denotes the 1-day lagged absolute daily excess return to the dollar factor, and EndofMonth_t is a dummy variable that takes the value of one on the last day of every month and zeroes otherwise. Here, the intercept α_0 measures the dollar risk factor's average absolute return on announcement days, while α_1 measures the difference between average absolute returns on the announcement and non-announcement days.

Table 3.1 presents the results from simple OLS regression of Equation (3.3). To test significance, we report asymptotic Newey-West standard errors in parentheses. In Column 1, we do not include the control variables and find that the occurrence of the trade news announcement, $Announcement_t$, is a significant positive predictor for the time variation in the absolute dollar factor. In Columns 2 and 3, we show that the estimated coefficient on the auto-regressive component, $|DOL_{t-1}|$, is positive and significant while the absolute currency market movement is not significantly higher on the last day of the month than other days. We then include the lagged currency market absolute return and the end-of-the-month dummy as controls in Columns 4 to 6. The announcement effect remains positive and significant in all specifications. This result suggests that the currency market movement is larger on trade news release days than on other days.

Table 3.1 Absolute dollar factor time-series regressions.

	(1)	(2)	(2)	(4)	(5)	(6)
Constant	0.255 (0.005)	0.226 (0.006)	0.256 (0.005)	0.225 (0.006)	0.255 (0.005)	0.225 (0.006)
$Announcement_t$	0.024 (0.012)			0.023 (0.013)	0.024 (0.012)	0.023 (0.013)
$ DOL_t $		0.118 (0.019)		0.118 (0.019)		0.118 (0.019)
$EndofMonth_t$			0.001 (0.075)		0.002 (0.017)	0.002 (0.016)
d.f.	6444	6445	6445	6444	6444	6442
Adj. $R^2\%$	1.38	-0.02	0.02	1.38	0.01	1.38

This table reports results for time-series regressions of the form: $|DOL_t| = \alpha_0 + \alpha_1 Announcement_t + \alpha_2 |DOL_{t-1}| + \alpha_3 EndofMonth_t + e_t$, where $|DOL_t|$ is the absolute percentage daily excess return to the dollar risk factor. The set of explanatory factors includes $Announcement_t$, a dummy variable that takes the value of one on trade news announcement days and zeroes otherwise, $|DOL_{t-1}|$, 1-day lagged absolute daily excess return to the dollar risk factor, $EndofMonth_t$, a dummy variable that takes the value of one on the last day of every month and zeroes otherwise. The data runs from March 1994 to December 2018. Numbers in parentheses denote Newey-West robust standard errors. We also report the degrees of freedom (d.f.) and adjusted R^2 in percentage.

3.4.1 Characterising trade news momentum returns

In this section, we present our main empirical results regarding the profitability and characteristics of the currency trade news momentum strategy, the difference between trade news momentum and past price momentum, and the difference between trade news momentum and carry trades.

Returns to trade news momentum strategy

Table 3.2 Panel A shows summary statistics for the five trade news momentum portfolios sorted on *CAR3s* around trade news releases, as well as for the long-short trade news momentum strategy, *CARMOM*. There is a sizeable spread (2.26%) in *CAR3s* around trade news releases. Consequently, the annualised average returns for the *CAR3*-sorted portfolios are increasing in *CAR3* from -2.19% for *Low* to 2.14% for *High*. This dispersion translates to a strong annualised excess return for the *HML* portfolio equal to 4.31% ($t = 2.68$). We also report the average difference between spot rate changes, Δs , for the high and low portfolios. Interestingly, the profitability of the trade news momentum strategy is also visible in spot rate changes themselves and is thus not mostly driven by the interest rate differential as is the case for carry trades. To measure the risk-adjusted returns, we also present annualised Sharpe ratio. The annualised Sharpe ratio of 0.54 is appealing in comparison to past price momentum, whose Sharpe ratio is 0.42 in Panel B.

Comparing to past price momentum strategy

The results presented above suggest that the trade news momentum strategy has creditable excess returns and Sharpe ratios. However, an important question is to what extent the trade news momentum strategy is different from the past price momentum documented in Menkhoff et al., 2012b.

To investigate this issue, we compute returns to the past price momentum (*PMOM*) and report descriptive statistics for the past price momentum in Panel B of Table 3.2. The average excess returns display an increasing pattern when moving from past loser to past winner, and the average excess return for a long-short strategy - the *HML* portfolio - is 3.94% per annum with a Sharpe ratio of 0.42. This profitable strategy form an interesting benchmark for our trade news momentum.

We first investigate if the trade news reaction signal also captures the spread in past performance. Panel A shows portfolios that sort currencies on the trade news reaction display a similar monotonic increasing pattern in the past performance but at a much smaller magnitude. The spread in lagged excess return for the trade news momentum portfolio is about 2.39%, which is positive but far less than the 5.95% spread reported for the past price momentum in Panel B. This suggests that part of the return from the trade news momentum strategy is related to past returns information, but part of it is driven by a different source of predictability which is in the market reaction regarding the trade news release but not in past performance.

In addition, we also examine other characteristics of trade news and past price momentum strategies. Comparing Panel A and B, while the portfolio turnover of the long-short past price and trade news momentum strategy can be roughly similar, we find that the two long-short portfolios are different in terms of their skewness and kurtosis. The trade news momentum only has a very small skewness of 0.01 (compared to 0.12 in price momentum) and a kurtosis around 4 (compared to over 6 in price momentum).

Comparing to the carry trade

It is instructive to compare the trade news momentum and the popular carry trade strategy in FX markets. Table 3.2 Panel C presents the descriptive statistics for the five portfolios sorted on currency forward discounts. There is a monotonically increasing pattern in average returns from low-interest-rate portfolio to high-interest-rate portfolio, and the average excess return for the long-short carry trade portfolio is 6.84% per annum with an SR of 0.77.

From the results of average spot rate returns (Δs), we can see that majority of the two momentum returns are coming from the spot rate changes while almost all of the carry trade returns are coming from the forward discount. In terms of portfolio turnover, over 77% of the components in the *Low* and *High* trade news momentum portfolios change at re-balancing while only less than 17% of the carry trade portfolios components change. Also, the carry trade produces negatively skewed (-0.47) excess return while the skewness is close to zero for the trade news momentum strategy.

More interestingly, the five carry trade portfolios also have a positive spread in *CAR3* and past performance, but the spread is much lower in magnitude than the two momentum strategies. Furthermore, the trade news momentum portfolios do have a positive spread in the forward discount, but the magnitude is much lower than that in the carry trade (1.17% compared to 10.38%), suggesting the trade news momentum return is also only partially related to interest rate information.

Overall, we document that currencies that receive positive market reactions following the trade news release have higher risk-adjusted returns than the currencies that receive adverse market reactions. We show from several perspectives that the trade news momentum is related to but distinct from the past price momentum or the carry trade strategies. In other words, the market's contemporaneous reactions to the trade news announcement are related but not identical to currencies' past performance or interest rate information.

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Table 3.2 Descriptive statistics of returns to currency trade news momentum.

Panel A: Trade News Currency Momentum Portfolios							
	<i>Low</i>	p2	p3	p4	<i>High</i>	<i>HML</i>	<i>AVG</i>
Mean%	-2.19	-0.14	1.07	2.11	2.14	4.31	0.69
<i>t</i>	(-1.23)	(-0.10)	(0.85)	(1.42)	(1.18)	(2.68)	(0.52)
Med%	0.02	1.65	1.82	2.23	0.38	4.57	2.15
SD%	8.81	7.53	6.24	7.40	8.99	7.94	6.61
Skew	-0.54	-0.55	-0.43	-0.08	0.16	0.01	-0.37
Kurt	5.45	5.09	4.28	4.39	5.35	4.25	4.62
AR1	0.08	0.00	0.05	0.10	0.12	0.06	0.09
SR	-0.25	-0.02	0.17	0.29	0.24	0.54	0.10
$\Delta s\%$	-3.95	-1.44	-0.24	0.50	-0.72	3.26	-1.04
Turnover	0.77				0.78		0.00
Mean $rx_{k,t}\%$	-1.17	-0.40	0.11	0.57	1.22		
Mean $(s - f)_{k,t}\%$	1.66	1.21	1.33	1.55	2.83		
Mean $CAR3_{k,t}\%$	-1.07	-0.42	0.03	0.49	1.19		
Panel B: Past Price Currency Momentum Portfolios							
	<i>Low</i>	p2	p3	p4	<i>High</i>	<i>HML</i>	<i>AVG</i>
Mean%	-1.39	-0.56	0.72	1.73	2.56	3.94	0.64
<i>t</i>	(-0.73)	(-0.36)	(0.56)	(1.12)	(1.54)	(2.11)	(0.48)
Med%	-0.20	2.04	1.77	1.32	3.24	2.03	2.13
SD%	9.50	7.72	6.38	7.70	8.27	9.31	6.61
Skew	-0.29	-0.97	-0.41	-0.32	0.23	0.12	-0.39
Kurt	6.03	7.30	5.14	6.97	5.41	6.35	4.63
AR1	0.00	0.04	0.07	0.12	0.10	0.03	0.09
SR	-0.15	-0.07	0.11	0.23	0.31	0.42	0.10
$\Delta s\%$	-2.98	-1.56	-0.58	0.00	-0.58	2.41	-1.08
Turnover	0.75				0.78		0.00
Mean $rx_{k,t}\%$	-2.91	-1.12	0.07	1.27	3.04		
Mean $(s - f)_{k,t}\%$	1.41	0.96	1.28	1.75	3.21		
Mean $CAR3_{k,t}\%$	-0.40	-0.17	0.03	0.25	0.50		
Panel C: Currency Carry Trade Portfolios							
	<i>Low</i>	p2	p3	p4	<i>High</i>	<i>HML</i>	<i>AVG</i>
Mean%	-2.56	-0.91	1.42	0.57	4.28	6.84	0.64
<i>t</i>	(-1.87)	(-0.68)	(1.03)	(0.33)	(2.15)	(3.80)	(0.48)
Med%	-2.68	-0.57	1.42	3.14	7.46	8.65	2.13
SD%	6.79	6.67	6.86	8.68	9.88	8.95	6.61
Skew	0.10	-0.13	-0.10	-1.41	-0.49	-0.47	-0.39
Kurt	4.06	4.34	4.51	9.23	6.35	4.56	4.63
AR1	0.05	0.09	0.06	0.12	0.11	0.15	0.09
SR	-0.38	-0.14	0.21	0.07	0.43	0.77	0.10
$\Delta s\%$	-0.47	-0.34	0.65	-2.55	-3.56	-3.10	-1.08
Turnover	0.17				0.15		0.00
Mean $rx_{k,t}\%$	-0.25	-0.12	0.11	0.13	0.45		
Mean $(s - f)_{k,t}\%$	-2.37	-0.59	0.79	3.06	8.01		
Mean $CAR3_{k,t}\%$	0.00	-0.03	0.03	0.06	0.15		

This table shows descriptive statistics for five trade news momentum (Panel A), five past price momentum (Panel B), and five carry trade (Panel C) portfolios. For each panel, we also report results for the average of all portfolios *AVG* and a long-short portfolio that long portfolio *High* and short portfolio *Low* (*HML*). Statistics include average and median annualised excess returns, annualised standard deviation, skewness, kurtosis, the 1st order autocorrelation coefficient of monthly excess return, annualised Sharpe ratios and average annualised pure spot rate returns (Δs). We also report the average sorting signals: lagged monthly excess returns rx , the cumulative three-day abnormal return $CAR3$, and lagged average annualised forward discount $f - s$ for currencies. Also shown are the turnover rate for the *Low*, *High* and *AVG* portfolios. The turnover rate is defined as the percentage of components in the portfolio change at re-balancing. The sample period is from March 1994 to December 2018.

3.4.2 Time-series analysis

We continue our investigation of the trade news momentum by taking a time-series perspective. We present the return correlation among different currency strategies and the time-series return regression results.

Return Correlations

As the first step in investigating the possible links among these currency strategies over time, Figure C.1 provides a graphical exposition of the excess returns accruing to investors. Figure C.1 shows cumulative excess returns for the *PMOM*, *CARMOM*, *CARRY* and *DOL* over the full sample period. Shaded areas correspond to NBER recessions. As illustrated by the figure, the two momentum strategies *PMOM* and *CARMOM* show some co-movement but are not perfectly correlated.

Table 3.3 shows correlation coefficients between returns to past price momentum portfolios, trade news momentum portfolios and carry trade portfolios. We always report the correlation between corresponding portfolios. For example, in row $\rho(PMOM, CARMOM)$ we report the correlation of the *Low* past price momentum portfolio with the *Low* trade news momentum portfolio in the first column, the correlation of the second *PMOM* portfolio and the second *CARMOM* portfolio in the second column, and so on for all five portfolios and the long-short portfolios *HML*.

Table 3.3 Correlation of trade news momentum, past price momentum and carry trade returns.

	<i>Low</i>	p2	p3	p4	<i>High</i>	<i>HML</i>
$\rho(PMOM, CARMOM)$	0.8046	0.8268	0.8389	0.7806	0.7532	0.3001
$\rho(PMOM, CARRY)$	0.5938	0.7847	0.8699	0.7703	0.6698	-0.1263
$\rho(CARMOM, CARRY)$	0.6155	0.7691	0.8446	0.7506	0.7508	-0.0639

This table shows the correlation coefficient between portfolio returns. Returns are based on five sorted portfolios and a long-short portfolio for past price momentum (*PMOM*), trade news momentum (*CARMOM*) and carry trade (*CARRY*). We only report correlations between corresponding pairs of portfolios. For example, in row $\rho(PMOM, CARMOM)$ we report the correlation of the *Low* past price momentum portfolio with the *Low* trade news momentum portfolio in column *Low*, the correlation of the second *PMOM* portfolio and the second *CARMOM* portfolio in column p2, and so on for all five portfolios and the long-short portfolios *HML*. The sample period is from March 1994 to December 2018.

It can be seen that the correlations of excess returns for the five portfolios of *PMOM* and *CARMOM* are high (around 70% to 83%), but the correlation between the long-short portfolios of *PMOM* and *CARMOM* are significantly lower at 30%. In terms of *CARMOM* and *CARRY*, the correlations of excess returns for their five portfolios are also high (around

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60% to 85%) but there is basically no correlation between their long-short portfolios (only -6.39%).

To further rationalise the correlations between the three currency strategies, Table 3.4 reports the composition of the trade news momentum (Panel A), past price momentum (Panel B), and carry trade (Panel C). It can be seen that the identity of the top ten currencies in corresponding portfolios of *PMOM* and *CARMOM* are similar, but the rankings are different. We also present the probability that a given currency enters simultaneously the same past price momentum and trade news momentum portfolio in column *match*. We find the match probability is low as none of them is over 0.148. For example, Panel A column *match* shows that there is a probability of 0.131 that NZD enters the *High* portfolio of *PMOM* and *CARMOM* simultaneously while there is a probability of 0.148 that JPY enters the *Low* portfolio of *PMOM* and *CARMOM* simultaneously.

Taken together, the correlation and portfolio composition results suggest that returns to the trade new momentum are imperfectly correlated with the returns of the carry trade and past price momentum.

Time-series regression

With the possible relation between the past performance and the market's reactions to the trade news release, we now turn to a more rigorous investigation using formal time-series regressions. This subsection shows that trade news currency momentum captures the past price currency momentum returns in time-series regressions.

These time-series regressions ask the question of which currency strategies, between those constructed using past performance and the measures of market reactions around trade news releases, generate significant alpha relative to the others. To this end, we regress the returns of a test strategy, taken from the set of currency strategies, onto the returns of explanatory strategies, which include the dollar risk factor, carry trade and the other currency strategies. Table 3.5 reports results for time-series regressions of the form:

$$y_t = \alpha + \beta'X_t + \varepsilon_t, \quad (3.4)$$

where the y_t are the monthly excess return to the past price momentum *PMOM* (Panel A), or trade news momentum *CARMOM* (Panel B) or the five portfolios (*Low* to *High*) of past price momentum (Panel C). The set of explanatory factors includes the monthly returns to the dollar factor *DOL*, carry trade *CARRY*, and the two momentum factors (*CARMOM* or *PMOM*). Newey-West robust standard errors are reported in parentheses.

Table 3.4 Portfolio composition.

Panel A: Trade News Momentum							
High				Low			
rank	currency	<i>freq</i>	<i>match</i>	rank	currency	<i>freq</i>	<i>match</i>
1	NZD	0.318	0.131	1	JPY	0.273	0.148
2	MXN	0.313	0.125	2	ZAR	0.259	0.088
3	AUD	0.293	0.071	3	CHF	0.236	0.108
4	JPY	0.264	0.091	4	AUD	0.212	0.081
5	HUF	0.257	0.118	5	NZD	0.209	0.088
6	ZAR	0.253	0.064	6	SEK	0.202	0.071
7	SEK	0.253	0.091	7	CZK	0.195	0.057
8	BRL	0.242	0.101	8	CAD	0.189	0.067
9	CZK	0.209	0.061	9	MXN	0.182	0.071
10	PLN	0.202	0.084	10	NOK	0.172	0.047
Panel B: Past Price Momentum							
High				Low			
rank	currency	<i>freq</i>	<i>match</i>	rank	currency	<i>freq</i>	<i>match</i>
1	NZD	0.381	0.131	1	JPY	0.333	0.148
2	MXN	0.294	0.125	2	CHF	0.249	0.108
3	HUF	0.273	0.118	3	AUD	0.226	0.081
4	BRL	0.269	0.101	4	HKD	0.199	0.054
5	AUD	0.262	0.071	5	ZAR	0.195	0.088
6	JPY	0.238	0.091	6	SEK	0.192	0.071
7	ZAR	0.236	0.064	7	NZD	0.178	0.088
8	CZK	0.228	0.061	8	MXN	0.175	0.071
9	PLN	0.212	0.084	9	SAR	0.172	0.047
10	SEK	0.212	0.091	10	CZK	0.165	0.057
Panel C: Carry Trade							
High			Low				
rank	currency	<i>freq</i>	rank	currency	<i>freq</i>		
1	ZAR	0.697	1	JPY	0.855		
2	BRL	0.559	2	CHF	0.815		
3	MXN	0.515	3	TWD	0.549		
4	HUF	0.478	4	SGD	0.347		
5	IDR	0.461	5	CZK	0.337		
6	INR	0.424	6	HKD	0.273		
7	RUB	0.347	7	SEK	0.219		
8	NZD	0.249	8	DKK	0.212		
9	PHP	0.232	9	ILS	0.131		
10	PLN	0.091	10	EUR	0.098		

This table reports the composition of the *High* and *Low* portfolios of the trade news momentum (Panel A), past price momentum (Panel B), and carry trade (Panel C). In each panel, we report the top ten currencies (with the frequency in column *freq*) entering each portfolio. We also present the probability that a given currency enters simultaneously the same past price momentum and trade news momentum portfolio in column *match*. For example, Panel A column *match* shows that there is a probability of 0.131 that NZD enters the *High* portfolio of *PMOM* and *CARMOM* simultaneously while there is a probability of 0.148 that JPY enters the *Low* portfolio of *PMOM* and *CARMOM* simultaneously. The sample period is from March 1994 to December 2018.

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Table 3.5 Time-series regressions of portfolio excess returns.

Panel A: Dependent, Past Price Momentum						Panel B: Dependent, Trade News Momentum					
	α	β_{dol}	β_{carry}	β_{carmom}	$R^2\%$		α	β_{dol}	β_{carry}	β_{pmom}	$R^2\%$
(1)	0.34 (0.15)	-0.15 (0.12)			0.87	(1)	0.36 (0.12)	0.03 (0.09)			-0.30
(2)	0.39 (0.18)		-0.10 (0.12)		0.60	(2)	0.36 (0.12)		-0.01 (0.08)		-0.34
(3)	0.21 (0.14)			0.36 (0.09)	8.87	(3)	0.27 (0.11)			0.26 (0.06)	8.87
(4)	0.25 (0.16)	-0.13 (0.10)	-0.07 (0.10)	0.36 (0.09)	10.02	(4)	0.26 (0.11)	0.06 (0.08)	0.00 (0.06)	0.26 (0.06)	8.54
Panel C: Dependent, Past Price Momentum P1-P5											
	α	β_{dol}	β_{carry}	β_{carmom}	$R^2\%$						
P1	-0.15 (0.10)	1.13 (0.06)	0.07 (0.06)	-0.18 (0.05)	67.44						
P2	-0.08 (0.06)	1.04 (0.05)	-0.01 (0.04)	-0.09 (0.03)	78.28						
P3	0.02 (0.04)	0.90 (0.03)	-0.02 (0.02)	0.02 (0.02)	86.07						
P4	0.11 (0.06)	1.01 (0.07)	-0.06 (0.03)	0.07 (0.03)	72.75						
P5	0.10 (0.09)	1.00 (0.06)	0.00 (0.05)	0.17 (0.06)	66.73						

This table reports results for time-series regressions of the form: $y_t = \alpha + \beta'X_t + \varepsilon_t$, where the y_t are the per cent monthly excess return to the past price momentum *PMOM* (Panel A), or trade news momentum *CARMOM* (Panel B) or the five portfolios of past price momentum P1-P5 (Panel C). The set of explanatory factors includes the percent monthly returns to the dollar risk factor *DOL*, carry trade *CARRY*, and the two momentum factors (*CARMOM* or *PMOM*). Newey-West Robust standard errors are reported in parentheses. We also report the adjusted R^2 in percentage. The sample period is from March 1994 to December 2018.

Considering the results for *PMOM* return as dependent variables in Panel A, specifications one and two show that the past price momentum factor generated a significant alpha at around 4.08% to 4.68% p.a. with t-statistic over two after considering the *DOL* and *CARRY* factor. Specifications three and four show that traditional past price momentum loads heavily on trade news momentum, even after controlling for the *DOL* and *CARRY* factors. Specifically, the estimated coefficients for *CARMOM* in specifications three and four are both 0.36 ($t = 4.10$). Also, the trade news momentum commands good explanatory power toward the past price momentum alpha. Indeed, the inclusion of the *CARMOM* factor as an explanatory variable drives the *PMOM*'s alpha to a statistically insignificant level of 21 bps (around 2.52% p.a.).

Panel B of Table 3.5 shows the regressions with trade news momentum *CARMOM* return as dependent variables. The trade news momentum is not explained by either return to *DOL* or *CARRY* and generates significant alphas of 36 bps per month (around 4.32% p.a.) with t-statistics around 3. In specifications three and four, the slope coefficient β_{pmom} estimate on price momentum is positive and statistically significant but is substantially different from unity (0.26). The R^2 s are less than 9%. Furthermore, the trade news momentum alpha is statistically different from zero in all specifications and economically sizeable (ranges from 4.32% to 3.12% p.a.), suggesting that *PMOM* and *CARMOM* are different from each other.

Panel C of Table 3.5 shows time-series beta estimates for the five past price momentum portfolios. Estimates of β_{carmom} are negative and significant for currencies with the worse past performance, whereas currencies with a better past performance co-move positively with the trade news momentum returns. There is a monotone increase in betas moving from the first to the fifth *PMOM* portfolios. This pattern indicates that investors expect high returns on the investment currencies in past price momentum as those currencies receive positive market reactions following trade news announcements. On the contrary, investors expect low returns on price momentum funding currencies as those currencies are perceived to be experiencing negative trade news.

3.5 Understanding the mechanism

In this section, we present a battery of additional exercises that explore what drives the excess returns to the trade balance news momentum.

To understand the economic mechanism behind the trade news momentum, recall from Table 3.4 that there is no intersection between the long and short legs' constituents of the carry trade. In contrast, the top ten currencies of the *High* and *Low* portfolios of the trade news momentum strategies are dominated by roughly the same set of currencies. This observation indicates that some currencies are more sensitive to trade balance news than others. Thus,

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to find out what is driving the excess returns to *CARMOM*, we need to understand the heterogeneity in currencies' exposure to trade balance news.

Central bank activity is a commonly cited reason for abnormal returns in foreign exchange markets. However, there is little evidence of the connection between currency price trends and central bank interventions. In this section, we try to show that the excess returns to the trade news momentum can be considered as costs to central banks who choose to intervene. Specifically, compared to broad-band FX regimes, currencies with narrow-band or fixed FX regimes are subject to more frequent central bank interventions with the primary goal of smoothing out or delaying any sudden exchange rate movements triggered by fundamental macroeconomic changes. The cost of dampened exchange rate volatility is non-random exchange rate movements, which create trading opportunities for trend-following forecasters.

We show this in two dimensions of central bank activities: capital account controls and exchange change rate regime choices. On the one hand, if a country chooses to impose heavy capital controls on trade, this will hinder the achievement of an equilibrium exchange rate through supply and demand. Then, news about an imbalance in trade will have a trending impact on its currency excess return, and we should expect to see a more robust trade news momentum mechanism. On the other hand, countries whose currencies are under a fixed exchange rate regime cannot automatically appreciate or depreciate when there is news of trade imbalances. Hence, trade balance news will have a more substantial impact, and we would expect to see a more potent trending mechanism on fixed regime currencies. That is to say, countries with a less open capital account or fixed exchange rate cannot afford an imbalance as much as other countries. Therefore, currencies under heavy central bank interventions should generate higher trade balance momentum profit.

To formally show this, we group all currencies into different subsamples: countries with open and closed capital accounts (denoted *open* and *close*) and countries with floating and fixed exchange rate regimes (denoted *float* and *fixed*).⁶ The hypothesis is that the trade news momentum should manifest itself stronger in subsamples of currencies with a higher degree of official intervention (i.e. countries with more capital control or fixed exchange rate) than a lower degree of intervention (countries with a very open capital account or floating exchange rate).

3.5.1 Capital account restrictions

To see if trade news momentum manifests itself stronger into heavy capital account restrictions, we compare the strategy performance constructed with the two subsamples of

⁶We exclude the Taiwan dollar from any further analysis due to missing data for the capital account openness index and exchange rate regime. Appendix C.1 provide details on subsamples.

currencies with *close* and *open* capital accounts. The performance of trade news momentum tends to be better in subsample *close* than *open*.

Table 3.6 shows descriptive statistics for trade news momentum (Panel A), past price momentum (Panel B), carry trade (Panel C) and dollar risk factor (Panel D) constructed with the full universe as well as various subsamples of currencies. We observe that the trade news momentum strategy has a higher mean excess return when constructed with currencies under heavier capital controls: 6.29% in *close* compared to 2.62% in *open*.⁷ Similarly, Figure 3.1 compares the Sharpe ratio of the trade news momentum constructed with different subsamples of currencies. The trade news momentum generates a higher annualised Sharpe ratio (0.43 versus 0.31) in subsample *close* than subsample *open*. On the contrary, the average excess return tends to be higher for the *PMOM* and *CARRY* portfolios constructed from currencies under less capital account controls: 3.19% in *open* compared to 2.51% in *close* for *PMOM*, and 7.52% in *open* compared to 5.67% in *close* for *CARRY*. The same pattern can be seen in Sharpe ratios. The strong performance of past price momentum in *open* is in line with Menkhoff et al. (2012b) where they find that price momentum is not primarily driven by currencies with investment limitations.

Does trade news momentum using subsamples of currencies perform well in explaining the returns to price momentum? Table 3.7 reports the time-series regression results where we regress the return of price momentum onto the returns of dollar factor, carry trade and trade news momentum. We repeat the regression with different samples of currencies. Panel B and C of Table 3.7 show the regression results with subsamples of *close* and *open*. First, across all subsamples, the OLS estimated coefficients of *CARMOM* are always positive and highly significant with t-statistics over 3. In line with our prediction, *CARMOM* factor from subsample *close* have larger explanatory power toward the price momentum than subsample *open* (β_{carmom} equals 0.31 with $t = 3.55$ in *close* compared to 0.25 with $t = 3.09$ in *open*). In both cases, *CARMOM* explains the price momentum alpha well. Though *PMOM* constructed from the subsample *close* does not generate a significant abnormal return in the first place, its alpha decreased from 23 bps to only four bps after the inclusion of the *CARMOM* factor.

Overall, subsamples of currencies with heavier capital account controls generate stronger trade news momentum performance and command more explanatory power toward the price momentum than the trade news momentum return constructed from currencies with an open capital account.

⁷Figure C.3 shows that the trade news momentum generates a higher cumulative return in subsample *close* than in subsample *open* or even full sample.

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Table 3.6 Trade news momentum and central bank activities.

	full	close	open	float	fixed	closefixed	closefloat	openfixed	openfloat
No. Max	27	8	21	23	9	3	7	6	17
No. Min	12	1	11	8	3	0	0	3	8
NaN%	0.00	11.78	0.00	0.00	0.00	48.82	14.81	0.00	0.00
Panel A: Trade News Currency Momentum									
Mean%	3.97	6.29	2.62	2.58	5.20	5.40	6.75	2.36	1.51
Median%	3.46	9.71	2.12	4.15	5.71	3.45	9.19	2.99	3.86
SD%	7.93	14.52	8.34	9.06	10.52	9.17	13.07	10.22	9.13
Skewness	0.00	-0.12	0.47	-0.28	0.21	0.91	-0.02	0.20	-0.41
Kurtosis	4.30	5.45	4.56	4.59	4.00	7.02	4.06	4.12	4.04
AR1	0.06	-0.02	0.12	0.00	0.03	-0.06	-0.05	0.08	0.04
SR	0.50	0.43	0.31	0.28	0.49	0.59	0.52	0.23	0.17
$\Delta s_t\%$	2.89	6.09	1.41	1.42	4.44	5.44	6.60	2.06	0.17
Panel B: Past Price Currency Momentum									
Mean%	4.12	2.51	3.19	1.96	3.96	1.60	2.92	3.34	2.51
Median%	1.81	3.97	0.59	2.09	4.13	1.71	5.68	2.14	4.40
SD%	9.26	16.00	9.18	10.35	10.84	10.40	14.74	10.88	10.33
Skewness	0.22	-0.16	0.45	0.14	-0.29	0.54	0.20	-0.08	0.22
Kurtosis	5.78	5.18	5.27	5.88	4.32	7.84	3.47	4.53	4.53
AR1	0.03	0.00	0.08	-0.02	0.03	0.04	0.11	0.04	0.05
SR	0.44	0.16	0.35	0.19	0.37	0.15	0.20	0.31	0.24
$\Delta s_t\%$	2.59	1.79	1.30	0.40	2.41	0.98	2.73	2.66	0.42
Panel C: Currency Carry Trade									
Mean%	6.93	5.67	7.52	8.34	5.59	3.95	3.16	4.09	9.56
Median%	10.58	8.52	10.48	9.28	8.59	2.56	5.54	5.83	11.80
SD%	8.89	13.27	9.91	10.21	9.94	9.01	13.70	10.43	10.95
Skewness	-0.52	-0.56	-0.78	-0.29	-0.89	0.62	-0.42	-1.05	-0.36
Kurtosis	4.52	4.59	4.83	4.60	7.70	5.68	4.02	8.05	4.28
AR1	0.17	-0.09	0.14	0.07	-0.02	0.07	0.04	0.07	0.14
SR	0.78	0.43	0.76	0.82	0.56	0.44	0.23	0.39	0.87
$\Delta s_t\%$	-2.90	-2.04	-1.15	-2.06	-1.38	0.29	-3.88	0.44	0.25
Panel D: Dollar Risk Factor									
Mean%	0.69	0.25	0.74	1.00	0.28	0.69	0.73	0.02	0.99
Median%	2.10	2.89	2.33	1.81	1.45	2.03	2.28	0.49	3.40
SD%	6.70	7.45	6.93	7.23	4.86	6.24	8.22	5.06	7.52
SR	0.10	0.03	0.11	0.14	0.06	0.11	0.09	0.00	0.13

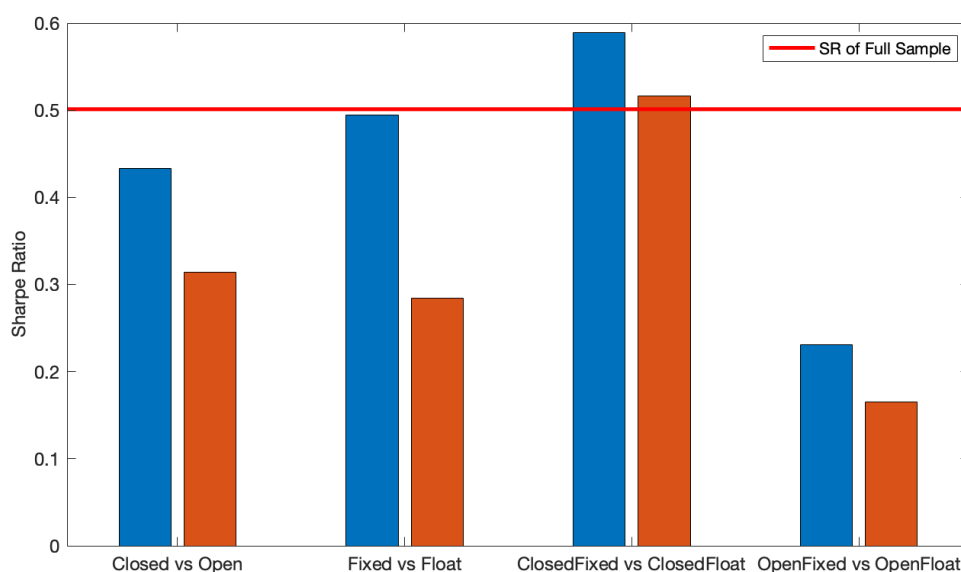
This table shows descriptive statistics for trade news momentum (Panel A), past price momentum (Panel B), carry trade (Panel C) and dollar risk factor (Panel D) constructed with the full sample as well as various subsamples of currencies. At each point in time, we only include currencies of countries which have a score smaller than zero (column *close*) or a score higher than zero (column *open*) in the capital account openness index of Chinn and Ito (2006). Column *float* is when we restrict our universe of currencies to have exchange rate regime 3 or 4 in the classification of Ilzetzki et al. (2019) while column *fixed* is when we restrict the universe of currencies to have exchange rate regime 1 or 2. We also report results for combinations of the above four subsamples. For example, column *closefixed* is when we restrict the universe of currencies to meet both criteria: have a score smaller than zero in the capital account openness index and have an exchange rate regime of 1 or 2. The top panel reports the maximum and the minimum number of available currencies over time, and NaN% is the percentage of time when there is no available investment currency. Descriptive statistics include annualised average and median excess returns, annualised excess return standard deviation, skewness and kurtosis, 1st order autocorrelation coefficient of monthly excess return, annualised Sharpe ratio, average annualised return from pure spot rate changes (Δs_t). The sample period is from 1994 to 2018.

Table 3.7 Time series regressions and central bank intervention.

This table reports results for time-series regressions of the form: $y_t = \alpha + \beta'X_t + \varepsilon_t$, where the y_t are the per cent monthly excess return to the past price momentum $PMOM$ constructed from the full sample of currencies (Panel A), or the $PMOM$ constructed from subsamples of currencies with the close or open capital account (Panel B and C), or $PMOM$ constructed from subsamples of currencies with fixed or floating exchange rate regime (Panel D and E). The set of explanatory factors includes the per cent monthly returns to the dollar risk factor DOL , carry trade $CARRY$ and trade news momentum $CARMOM$ constructed from corresponding samples as the dependent variable. For example, in Panel B, the dependent variable is $PMOM$ constructed from currencies with a close capital account, the explanatory factors are also constructed from the same subsample of currencies. Newey-West Robust standard errors are reported in parentheses. We also report the adjusted R^2 in percentage. The sample period is from 1994 to 2018.

Panel A: Full Currency Universe					
	α	β_{dol}	β_{carry}	β_{carmom}	$R^2\%$
(1)	0.35 (0.15)	-0.15 (0.12)			0.89
(2)	0.39 (0.18)		-0.08 (0.12)		0.32
(3)	0.23 (0.14)			0.34 (0.09)	8.28
(4)	0.27 (0.17)	-0.14 (0.10)	-0.05 (0.10)	0.34 (0.09)	9.18
Panel B: Capital Account Openness Index < 0, <i>close</i>					
	α	β_{dol}	β_{carry}	β_{carmom}	$R^2\%$
(1)	0.23 (0.30)	-0.63 (0.17)			8.16
(2)	0.34 (0.31)		-0.24 (0.11)		3.50
(3)	0.04 (0.27)			0.31 (0.09)	7.45
(4)	0.11 (0.27)	-0.48 (0.15)	-0.12 (0.11)	0.29 (0.08)	14.63
Panel C: Capital Account Openness Index > 0, <i>open</i>					
	α	β_{dol}	β_{carry}	β_{pmom}	$R^2\%$
(1)	0.27 (0.15)	-0.05 (0.13)			-0.20
(2)	0.27 (0.17)		-0.01 (0.10)		-0.33
(3)	0.22 (0.14)			0.25 (0.08)	4.84
(4)	0.22 (0.16)	-0.06 (0.11)	0.01 (0.08)	0.25 (0.08)	4.40
Panel D: Fixed Exchange Rate Regime, <i>fixed</i>					
	α	β_{dol}	β_{carry}	β_{carmom}	$R^2\%$
(1)	0.34 (0.18)	-0.24 (0.24)			0.81
(2)	0.42 (0.18)		-0.19 (0.11)		2.60
(3)	0.26 (0.17)			0.17 (0.08)	2.44
(4)	0.34 (0.17)	-0.12 (0.21)	-0.16 (0.09)	0.15 (0.07)	4.52
Panel E: Floating Exchange Rate Regime, <i>float</i>					
	α	β_{dol}	β_{carry}	β_{pmom}	$R^2\%$
(1)	0.18 (0.16)	-0.14 (0.10)			0.58
(2)	0.13 (0.17)		0.06 (0.09)		-0.04
(3)	0.13 (0.16)			0.25 (0.09)	4.57
(4)	0.09 (0.16)	-0.15 (0.11)	0.08 (0.09)	0.25 (0.09)	5.38

Fig. 3.1 Sharpe ratio and central bank intervention.



This figure compares the Sharpe ratio of trade news momentum constructed with different subsamples. The red line shows the level of Sharpe ratio of the trade news momentum constructed with the full sample of currencies. Each bar shows the Sharpe ratio of the trade news momentum constructed with the subsamples labelled below. For example, ‘closed’ and ‘open’ represent currencies of countries with close and open capital accounts, respectively. And ‘fixed’ and ‘float’ represent currencies with fixed and floating exchange rate regimes, respectively. Moreover, ‘closedfixed’ represent currencies with both high level of capital controls and fixed exchange rate regimes.

3.5.2 Exchange rate regime choices

To see how the trade news momentum performance under different exchange rate regimes, we compare the results from subsamples of currencies with *float* and *fixed* exchange rate regimes.

Compare column *float* and *fixed* in Table 3.6, trade news momentum has better performance in terms of mean return and Sharpe ratio when constructed with fixed exchange rate currencies than floaters: mean return is 5.2% in *fixed* compared to 2.58% in *float*, and Sharpe ratio is 0.49 in *fixed* compared to 0.28 in *float*.⁸ More interestingly, in line with the previous results, we find that subsamples of *openfixed* outperform the *openfloat* sample as shown in Figure 3.1. Hence, the under-performance of the subsamples with open economies could be partially attributed to the floaters as the majority of currencies with an open capital account are floaters.

⁸The cumulative return in Figure C.4 shows that the trade news momentum achieves a higher cumulative excess return in subsample *fixed* than subsamples *float* or full sample.

In Table 3.7 Panel D and E, both *CARMOM* factors from subsamples *fixed* and *float* command positive and significant estimated coefficients toward price momentum return. In Panel D, the *CARMOM* factor explains the price momentum well in specification three; however, it no longer captures all the price momentum alpha with the effect of the *DOL* and *CARRY* factors in specification four. In Panel E, though the price momentum does not have a significant alpha, trade news momentum from subsamples of floaters halved the price momentum alpha from 18 bps to 9 bps after controlling for *DOL* and *CARRY* factors.

In this section, we show that the subsample of currencies with fixed exchange rates exhibits stronger trade news momentum performance than the subsample of currencies with floating exchange rates. Previously, we also showed that currencies with heavier capital account controls generate stronger trade news momentum than currencies with an open capital account. These empirical findings align with our hypothesis that currencies with a higher degree of central bank interventions (capital control or fixed exchange rate) generate stronger trade news momentum than those with less. These findings also support the argument that the ‘lean-against-the-wind’ style of official intervention with the aim to smooth out or delay sudden exchange change rate movement creates a predictable trend in the FX market. Hence, investors could view the excess returns to trade news momentum as profit earned against the central banks who choose to intervene more.

3.6 Conclusion

This paper documents the importance of trade balance news in explaining past price currency momentum returns. It has been well studied that the past price momentum, which relies on return continuation among winner and loser currencies, generates puzzling high excess returns. We find that a strategy based on US trade data announcements - longing currencies with positive market reactions and shorting currencies with adverse market reactions around trade news announcements - explains the performance of past price momentum. In contrast to an explanation based on compensation for risk, we find evidence that links trade news momentum profits to the level of central banks’ activity. In this sense, trade news momentum provides a trading opportunity for trend-followers to profit from non-random movements in currencies subject to heavy official controls.

We show that trade news momentum returns are positively but imperfectly correlated with past price momentum returns. As price momentum primarily aims at exploiting past cross-sectional trend continuation, it may be expected that returns to this strategy are closely related to our trade news momentum constructed from contemporaneous market reactions. Although returns to past price and trade news momentum correlate at 30%, these two strategies are

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different in terms of their portfolio return characteristics, spreads in their corresponding sorting criteria and portfolio composition. Moreover, trade news momentum is distinct from the carry trade in the FX markets because of their relatively small return correlation. Importantly, trade news momentum has positive and significant alphas relative to the price momentum and carry trade returns. Trade news momentum also commands high explanatory power toward the price momentum alpha.

Empirically, using subsamples of currencies of countries with different capital accounts and exchange rate regimes, we find that trade news momentum manifests itself stronger in currencies under heavier central bank interventions. Currencies under interventions not only deliver higher trade news momentum profit but consistently retain their high explanatory power towards the performance of past price momentum. In sum, extending the findings in stock markets, our paper is the first to show that the price momentum anomaly manifests itself in currencies' heterogeneity in reactions to the US trade figure releases. Trade figure announcements create an increase in trade imbalance uncertainty and pose a more significant impact on the price of currencies under heavy capital account controls or exchange rate interventions.

Concluding remarks

This thesis contributes to the literature at the intersection of international macro-finance and empirical asset pricing. The three chapters present an empirical investigation of the movement in the cross-section of asset returns around the world concerning global inflation risk, the US monetary policy, and the US trade balance news announcements.

The first chapter studies the global inflation risk in the international equity market. This chapter shows that global inflation risk is priced in the international equity returns and that this global inflation risk premium is strongly time-varying and has increased markedly since the 2008 global financial crisis. To understand the time variation, I document new empirical evidence of a simultaneous shift in the global inflation risk premium and the cyclical nature of inflation. Reconciling the novel finding, this study investigates a mechanism that as the severity of the ZLB varies the feasibility of the traditional stabilisation policy, the cyclical properties of inflation fluctuate correspondingly. Away from the ZLB, when changes in the monetary policy rate broadly neutralise demand fluctuations, supply shocks driven inflation is counter-cyclical and contains bad news for future consumption. As a result, high inflation beta assets provide a hedge against bad states, and the inflation risk premium is thus negative. However, the study shows that the 2008-2009 financial crisis appeared as a particularly large demand shock accompanied by ZLB limitation, leading to a pro-cyclical inflation regime. Thus, assets with lower inflation betas are more attractive to hedge, and the inflation risk premium shifted positively.

The second chapter focuses on the impact of the US monetary policy on currencies. To distil the pure monetary policy effect on currencies, the chapter purges the monetary policy from the contemporaneous information shocks by analysing the co-movement of interest rates and stock prices in a narrow policy announcement window. The study illustrates that currencies tend to depreciate on tightening policy shocks but tend to appreciate when there are contemporaneous positive information shocks. Also documented is that fundamental variables like interest rate differentials help explain currencies' heterogeneous responses in the cross-section. Motivated by these two findings, the chapter constructs an "exposure index" that captures the cross-sectional and time-series difference in sensitivity to the

Concluding Remarks

different structural shocks among currencies. The resulting exposure indices show that US monetary policy-related shocks have a larger impact on currencies of countries that are net borrowers, peripheral in the global trade network, characterised by higher interest rates, and on currencies with higher equity beta. Long-short portfolios that sort currency by the different exposure indices are constructed to evaluate the economic magnitude of the monetary policy effects. The findings show that currencies that are more sensitive to the US monetary policy earn significantly higher average returns than less sensitive currencies. An aggregate policy exposure strategy generates a significant annualised abnormal return of 3.47% after controlling for the dollar and carry factors. The exposure strategy performance implies that monetary policy's effect on currency is economically important; thus, investors require compensation to hold the currencies more exposed to the US monetary policy.

The third chapter turns to understand currency momentum by studying how different currencies are related to fundamental information in the form of trade balance news. The chapter introduces a macro fundamental currency momentum - trade news momentum - by longing the currencies that receive positive market reactions and shorting the currencies that receive adverse market reactions to the US trade news releases. The study finds a large annualised Sharpe ratio to the trade news momentum of 0.54 per annum. The time-series regressions suggest that the returns trade news momentum are positively but imperfectly correlated with the returns past price momentum. Notably, the trade news momentum commands strong explanatory power toward the past price momentum alpha. Further analysis of the cross-section of sorted portfolios implies that the cross-section predictability of currency's past performance can be interpreted by the corresponding movements in fundamentals, captured by the cross-currency spread in market reactions to the trade news announcement. The chapter continues to investigate what drives the heterogeneity in currencies' exposure to trade news. It finds that trade news momentum manifests itself stronger in currencies under heavier central bank interventions. These findings support the argument that currencies under interventions can afford less trade imbalance and their excess return movement are predictable. Thus, the profitability of trade news momentum can be reconciled with the costs to central banks.

Appendix A

A.1 Historical decomposition of the inflation driver

To provide empirical evidence to the mechanism proposed in Section 1.3.2, I estimate the role of the different shocks in driving the increase in the US inflation developments from 1960 to 2019 using historical decomposition. Stock and Watson (2001) infer the causal influence of monetary policy on unemployment and inflation in a three-variable VAR, ordered as 1) inflation (π_t), 2) the unemployment rate (u_t), and 3) the interest rate (r_t).¹ The first key identifying assumption is that the federal funds rate reacts contemporaneously to movements in inflation and in unemployment. The second assumption is that the monetary policy shocks (ε_t^{MonPol}) do not affect inflation and unemployment within the same period of the shock. An empirical application by Cesa-Bianchi (2021) assumes a VAR with $p = 4$, and the system becomes

$$\begin{pmatrix} \pi_t \\ u_t \\ r_t \end{pmatrix} = \sum_{p=4} \Phi_p x_{t-p} + \begin{pmatrix} b_{11} & 0 & 0 \\ b_{21} & b_{22} & 0 \\ b_{31} & b_{32} & b_{33} \end{pmatrix} \begin{pmatrix} \varepsilon_t^1 \\ \varepsilon_t^2 \\ \varepsilon_t^{MonPol} \end{pmatrix}. \quad (\text{A.1.1})$$

To interpret the three shocks, the impulse responses² for the recursive VAR, ordered π_t, u_t, r_t are plotted in Figure A.1 to A.3. Figure A.1 shows that an unexpected increase in inflation (ε_t^1) leads to a combination of higher inflation, rising unemployment and increased fed funds rate, mimicking the effect of a negative aggregate supply shock. On the other hand, Figure A.2 shows that an unexpected increase in unemployment (ε_t^2) leads to a combination

¹I update the data to cover the period from 1960Q1 to 2019Q1. The inflation data are computed as $\pi_t = 400 \ln(P_t/P_{t-1})$, where P_t is the GDP chain-type price index, and u_t is the unemployment rate retrieved from FRED, Federal Reserve Bank of St. Louis. Quarterly data on u_t and the federal funds rate are formed by taking quarterly averages of their monthly value.

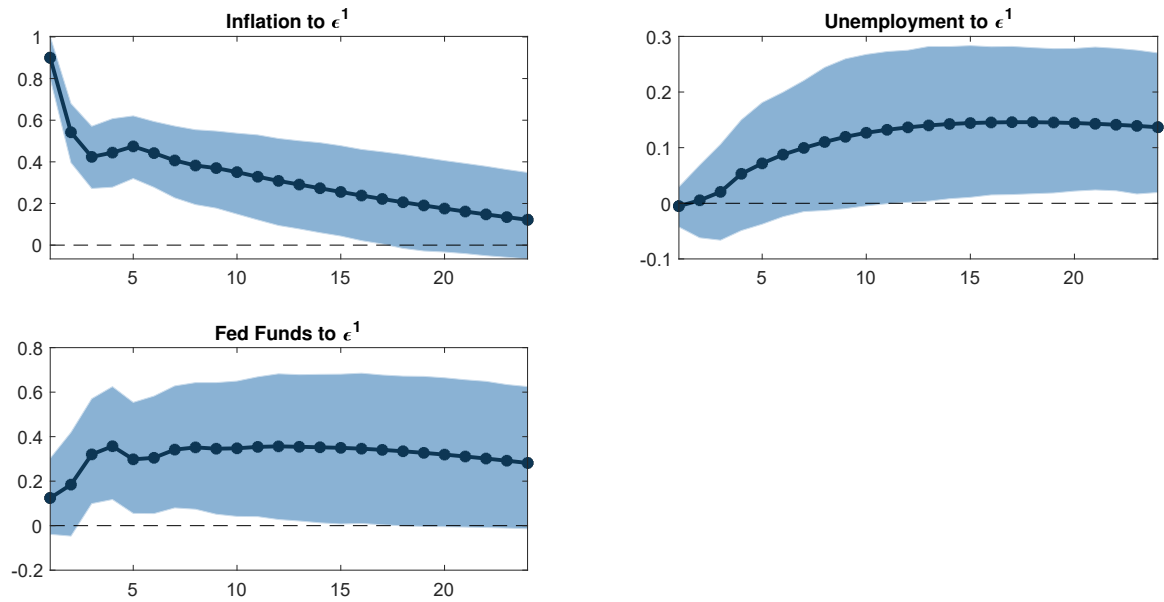
²Impulse responses and the later historical decomposition estimations are implemented using the VAR toolbox by Ambrogio Cesa-Bianchi, available at <https://github.com/ambropo/VAR-Toolbox>.

of lower inflation, higher unemployment and decreased fed fund rates, mimicking the effect of a negative aggregate demand shock. Additionally, Figure A.3 illustrates that monetary policy shock raises inflation in the short run (price puzzle) and increases unemployment.

In Figure A.4 to A.6, I present the historical decomposition of the three variables, showing the estimated contribution of each shock to deviations of the variables from their steady state at each point in time. It is clear that supply shocks (ε_t^1) were particularly important during the 1970s and that the contribution of monetary policy shock was relevant during the Volcker era of 1979-1982. However, the financial crisis of 2008-2009 appears as a particularly large demand shock (ε_t^2). In fact, the post-2000 decade was characterised by an environment in which large supply shocks were absent, and the major recessions were driven by demand shocks.

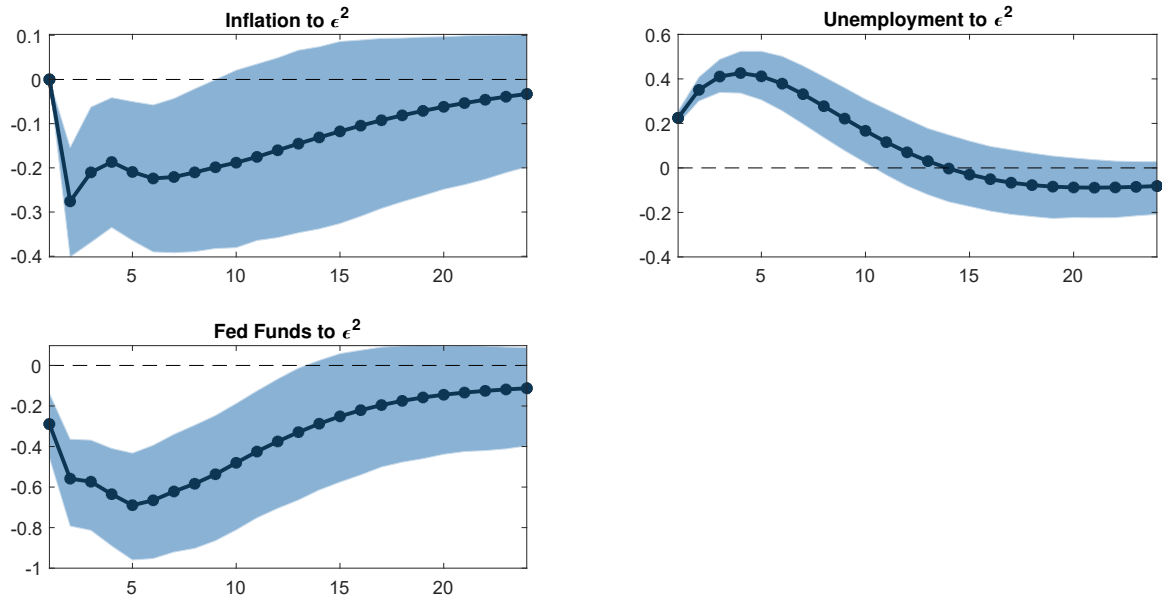
A.1 Historical decomposition of the inflation driver

Fig. A.1 Impulse response of negative supply shocks.



This figure reports the impulse responses of an unexpected increase in inflation for the inflation-unemployment-interest rate recursive VAR, ordered π_t, u_t, r_t . The model is estimated over the sample 1960Q1 – 2019Q1.

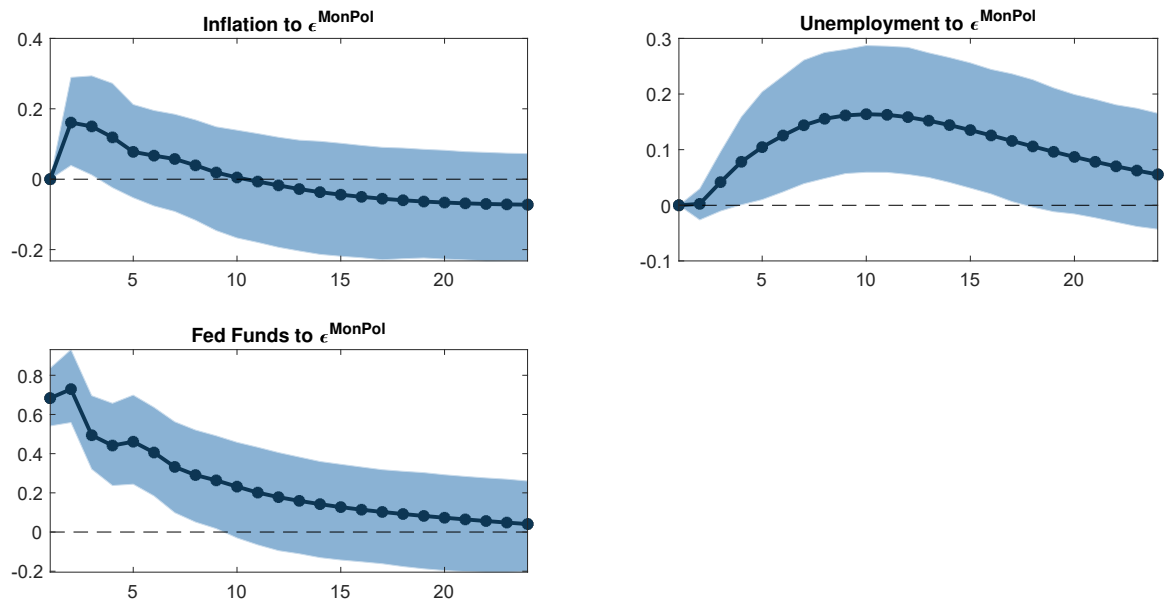
Fig. A.2 Impulse response of negative demand shocks.



This figure reports the impulse responses of an unexpected increase in unemployment for the inflation-unemployment-interest rate recursive VAR, ordered π_t, u_t, r_t . The model is estimated over the sample 1960Q1 – 2019Q1.

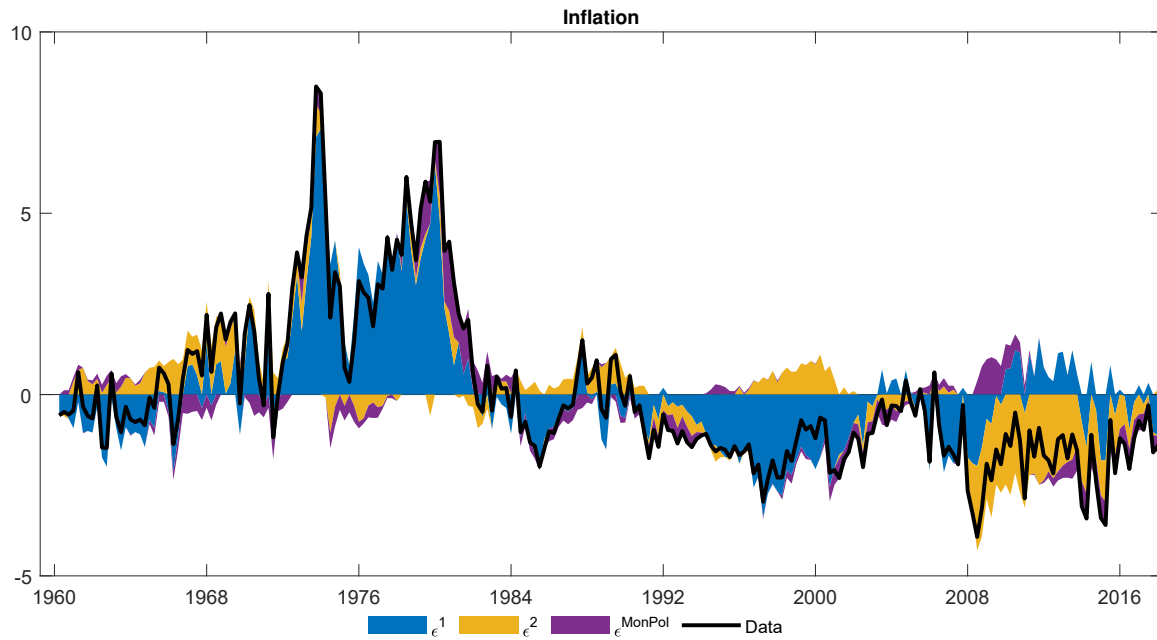
A.1 Historical decomposition of the inflation driver

Fig. A.3 Impulse response of monetary policy shocks.



This figure reports the impulse responses of an unexpected increase in the federal funds rate for the inflation-unemployment-interest rate recursive VAR, ordered π_t, u_t, r_t . The model is estimated over the sample 1960Q1 – 2019Q1.

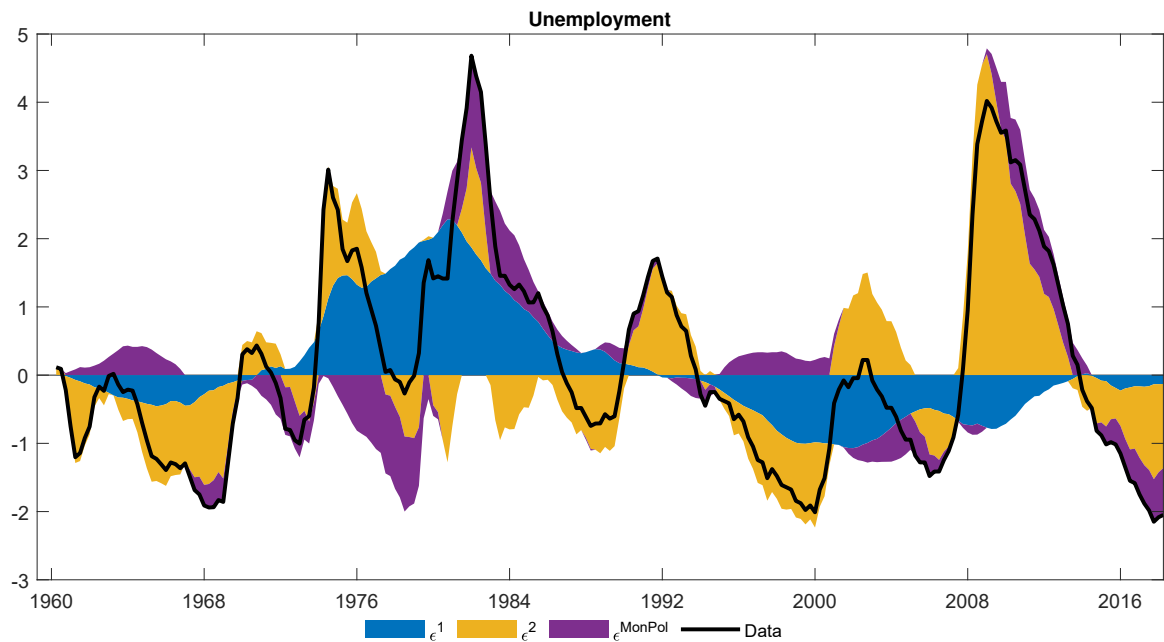
Fig. A.4 Historical decomposition of inflation.



This figure reports the historical decomposition of US inflation. The black line is the difference between the actual series and the steady state obtained by the VAR model. The coloured areas denote the contribution of the considered structural shock. The model is estimated over the sample 1960Q1 – 2019Q1.

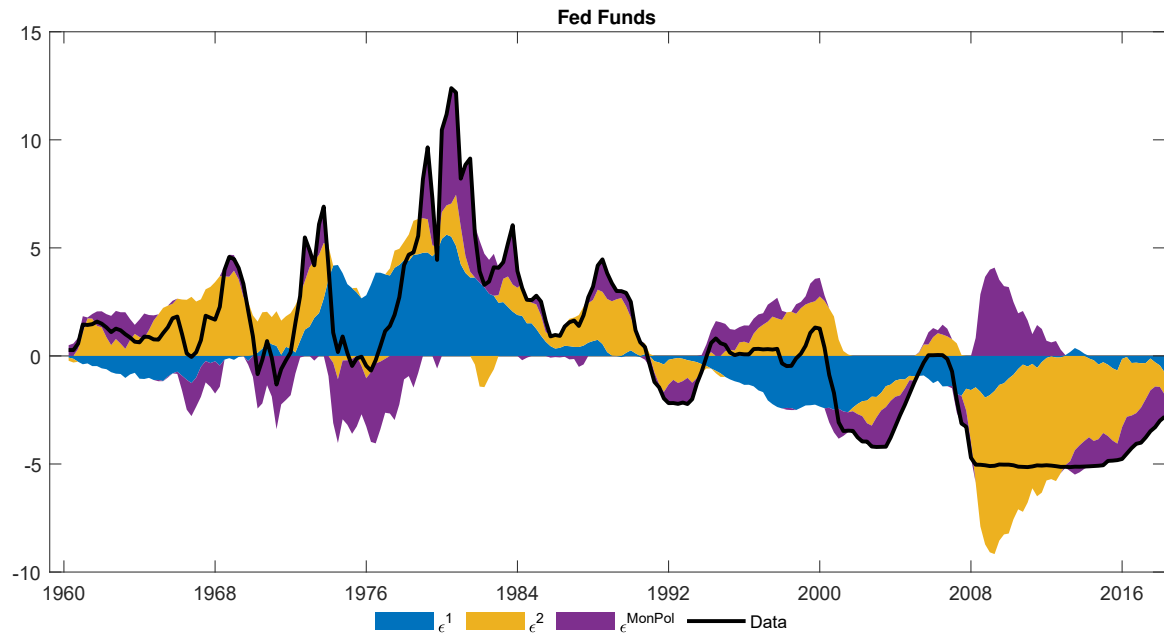
A.1 Historical decomposition of the inflation driver

Fig. A.5 Historical decomposition of the unemployment rate.



This figure reports the historical decomposition of US unemployment rate. The black line is the difference between the actual series and the steady state obtained by the VAR model. The coloured areas denote the contribution of the considered structural shock. The model is estimated over the sample 1960Q1 – 2019Q1.

Fig. A.6 Historical decomposition of the federal fund rate.



This figure reports the historical decomposition of the US federal funds rate. The black line is the difference between the actual series and the steady state obtained by the VAR model. The coloured areas denote the contribution of the considered structural shock. The model is estimated over the sample 1960Q1 – 2019Q1.

A.2 Inflation decomposition

This section describes the methodology adopted for inflation seasonality adjustment and for extracting the trend and unexpected inflation. Note that all the models below are estimated in “pseudo-real-time” using expanding windows, with the first window covering 36-quarters of observations.

A.2.1 Seasonality adjustment

I adjust the raw inflation data for seasonality by modelling a trigonometric seasonal pattern as in Harvey (2006a) and Harvey (2006b).

A.2.2 Estimating inflation surprise

I extract the trend inflation and unexpected inflation by adopting the unobserved components model with stochastic volatility (UC-SV) *à la* Stock and Watson (2007) and Stock and Watson (2016). The rate of inflation, π_t , has a stochastic trend τ_t and a disturbance term η_t . In the UC-SV model, the variance of the permanent and transitory disturbances evolve randomly over time. Specifically, logarithms of the variance of η_t and ε_t evolve as an independent random walk. The UC-SV model is,

$$\begin{aligned}\pi_t &= \tau_t + \eta_t, \quad \text{where} \quad \eta_t = \sigma_{\eta,t} \xi_{\eta,t}, \\ \tau_t &= \tau_{t-1} + \varepsilon_t, \quad \text{where} \quad \varepsilon_t = \sigma_{\varepsilon,t} \xi_{\varepsilon,t}, \\ \ln \sigma_{\eta,t}^2 &= \ln \sigma_{\eta,t-1}^2 + v_{\eta,t}, \\ \ln \sigma_{\varepsilon,t}^2 &= \ln \sigma_{\varepsilon,t-1}^2 + v_{\varepsilon,t},\end{aligned}\tag{A.2.1}$$

where $\xi_t = (\xi_{\eta,t}, \xi_{\varepsilon,t})$ is i.i.d. $N(0, I_2)$, $v_t = (v_{\eta,t}, v_{\varepsilon,t})$ is i.i.d. $N(0, \gamma I_2)$, and γ is a parameter. Then, the unexpected inflation u_t can be derived as

$$\begin{aligned}u_t &= \pi_t - E_{t-1}[\pi_t] \\ &= \pi_t - \tau_{t-1}.\end{aligned}\tag{A.2.2}$$

A.3 Bootstrap algorithm

The block-bootstrap algorithm associated to the regression of Tables 1.2, 1.3, 1.5, 1.6 in the paper consists of the following steps.

1. In each replications $m = 1, \dots, 1000$, I construct pseudo-samples for both consumption growth and inflation by drawing with replacement T_m overlapping n -quarter blocks from:

$$\{\Delta C_{t+1:t+n+1}^m, \Pi_{t:t+n}^m\}, \quad t = s_1^m, s_2^m, \dots, s_{T_m}^m, \quad (\text{A.3.1})$$

where the time indices, $s_1^m, s_2^m, \dots, s_{T_m}^m$, are drawn randomly from the original time sequence $1, \dots, T$. For each universe (US, G7 or OECD), the n -quarter block size is chosen according to the Politis and White (2004) and Patton et al. (2009)'s estimators of the optimal block size for the moving blocks bootstrap method. I join these blocks to construct a quarterly time series matching the length of the sample from June 1970 to September 2019. The common start date of June 1970 is selected to match the OECD data availability.

2. For $m = 1, \dots, 1000$, I run the two-stage tests described in Section 3 for the artificial data:

$$\Delta C_{s+1}^m = a_{m,t}^{1Q} + b_{m,t}^{1Q} \Pi_s^m + e_{s+1}^m, \quad \text{for } s = 1, \dots, t-1, \quad (\text{A.3.2})$$

$$\Delta C_{t+1}^m = d_{m,0}^{c,1Q} + d_{m,1}^{c,1Q} (\hat{a}_{m,t}^{1Q} + \hat{b}_{m,t}^{1Q} \Pi_t^m) + e_{t+1}^m, \quad (\text{A.3.3})$$

and save the estimates $b_{m,t}^{1Q}$, $d_{m,0}^{c,1Q}$, and $d_{m,1}^{c,1Q}$. The bootstrapped standard errors reported in Table 1.2 are calculated as the standard deviation of $d_{m,0}^{c,1Q}$, and $d_{m,1}^{c,1Q}$ over the 1000 bootstrap replications (Horowitz, 2019). The bootstrap estimates, $b_{m,t}^{1Q}$, represent the artificial nominal-real covariance that is going to be used to get the bootstrapped standard errors for the remaining tables of the paper.

3. Using the same time indices $s_1^m, s_2^m, \dots, s_{T_m}^m$, I re-sample the FFR and SSR the same way used for consumption growth and inflation, such that:

$$\{I_{t-1:t+n-1}^{m,FFR}, I_{t-1:t+n-1}^{m,SSR}\}, \quad t = s_1^m, s_2^m, \dots, s_{T_m}^m. \quad (\text{A.3.4})$$

Notice that the characteristics are lagged just like in the data. I join these blocks to construct 1000 artificial interest rate files matching the length of my sample.

4. I use the the 1000 bootstrap estimates, $b_{m,t}^{1Q}$, as the main proxy for the nominal-real covariance, $NRC_{m,t+1}$. Then, I run the test on the role of expected ZLB duration:

$$\begin{aligned} b_{m,t}^{1Q} &= \alpha_{m,t} + \beta_{m,1} b_{m,t-1}^{1Q} + \varepsilon_t^m, \\ \alpha_{m,t} &\equiv \beta_{m,0} + \beta_{m,2} I_{t-1}^m, \end{aligned} \quad (\text{A.3.5})$$

and save the estimates $\beta_{m,0}$, $\beta_{m,1}$ and $\beta_{m,2}$. The bootstrapped standard errors reported in Table 1.3 are calculated as the standard deviation of $\beta_{m,0}$, $\beta_{m,1}$ and $\beta_{m,2}$ over the 1000 bootstrap replications.

5. Using the same time indices $s_1^m, s_2^m, \dots, s_{T_m}^m$, I re-sample all country equity indices $i = 1, \dots, I$ in the MSCI files. To be consistent with the data, I bootstrap both returns, $R_{t+1} = \{R_{1,t+1}, R_{2,t+1}, \dots, R_{I,t+1}\}'$, and Fama-French factors, $Z_{t+1} = \{MKT_{t+1}, SMB_{t+1}, HML_{t+1}\}$, such that:

$$\{R_{t+1:t+n+1}^m, Z_{t+1:t+n+1}^m\}, \quad t = s_1^m, s_2^m, \dots, s_{T_m}^m. \quad (\text{A.3.6})$$

I join these blocks to construct 1000 artificial MSCI files matching the length of my sample.

6. In each replication, I estimate at the end of month t and for each artificial index i its exposure to innovations in inflation. The inflation betas are estimated using the WLS-Vasicek procedure described in Section 4 of the paper. I only estimate inflation beta, $\beta_{\Pi,i,t}^m$, if an artificial index return series has at least 24 out of the last 60 months of returns available.
7. For $m = 1, \dots, 1000$ and at the end of each month t , I then sort the artificial indices on these inflation betas to construct the five equal-weighted inflation beta-sorted portfolios that feature prominently in the paper, $R_{p,t+1}^m = \{R_{High,t+1}^m, R_{2,t+1}^m, \dots, R_{Low,t+1}^m\}$. The two bootstrap estimates of the inflation risk premium are constructed as follows. First, I take the high- minus-low spreading portfolio from this sort: $R_{IPHL,t+1}^m = R_{High,t+1}^m - R_{Low,t+1}^m$. Second, I construct the rank-weighted inflation beta-sorted portfolios ($R_{IPRW,t+1}^m$) as described in Section 4 of the paper.
8. For each replication, I then run the predictive regression described in Section 4.3. of the paper. That is, I regress returns on the artificial inflation portfolios and risk premia (compounded over horizons $K = 1, \dots, 4$ quarters) on the lagged nominal-real covariance (i.e., the bootstrap coefficient estimate $b_{m,t}^{1Q}$ from Step 2 above) using:

$$R_{p,t+2:t+2+K}^m = L_{m,0} + L_{m,NRC} b_{m,t}^{1Q} + \varepsilon_{t+2:t+2+K}^m. \quad (\text{A.3.7})$$

Note that the timing in the different steps of the bootstrap is consistent with the data, so that the left-hand side returns are observed strictly after the consumption and inflation numbers used to estimate the right-hand side nominal-real covariance. I use the standard deviation of the estimates $L_{m,0}$ and $L_{m,NRC}$ over the 1000 bootstrap replications as the standard error for the predictive regressions of Table 1.5.

9. Finally, I run the pooled predictive regressions described in Section 5.1. of the paper. That is, I regress returns on the artificial inflation beta-sorted five portfolios, $p = High, 2, 3, \dots, Low$ on their time-varying inflation betas ($\beta_{\Pi,p,t}^m$), the nominal-real covariance, and an interaction:

$$R_{p,t+3}^m = L_{m,0} + L_{m,\beta_{\Pi}} \beta_{\Pi,p,t}^m + L_{m,NRC} b_{m,t}^{1Q} + L_{m,\beta_{\Pi} \times NRC} (\beta_{\Pi,p,t}^m \times b_{m,t}^{1Q}) + \epsilon_{t+3}^m. \quad (A.3.8)$$

I save the estimates $L_{m,0}$, $L_{m,\beta_{\Pi}}$, $L_{m,NRC}$ and $L_{m,\beta_{\Pi} \times NRC}$. The bootstrapped standard errors reported in Panel A of Table 1.6 are calculated as the standard deviation of $L_{m,0}$, $L_{m,\beta_{\Pi}}$, $L_{m,NRC}$ and $L_{m,\beta_{\Pi} \times NRC}$ over the 1000 bootstrap replications. I also evaluate the joint significance of the variables by performing inference on the predicted risk premia when $\beta_{\Pi,p,t}^m$ and $b_{m,t}^{1Q}$ are at plus or minus one standard deviation from their respective means in the block-bootstrapped sample. I use the standard deviation of these predicted risk premia to calculate the t -statistics for the estimates reported in Panel B of Table 1.6.

A.4 Model derivations

Some derivations and equations below are cited and summarised from Boons et al. (2020).

A.4.1 The nominal-real covariance

Another way to write Equation (1.4) is

$$\begin{aligned} NRC_{t+1} &= NRC_{t+1}^a + NRC_{t+1}^b, \\ NRC_{t+1}^a &\equiv \beta_0 + \beta_1 NRC_t^a + \varepsilon_{t+1}, \\ NRC_{t+1}^b &\equiv \beta_1 NRC_t^b + \beta_2 I_t^{SSR}, \end{aligned} \tag{A.4.1}$$

where the process for the nominal-real covariance (NRC_{t+1}) is decomposed into two independent parts: (i) NRC_{t+1}^a follows the simple mean-reverting process, (ii) and NRC_{t+1}^b governs the time-varying level of nominal-real covariance through the shadow rate (I_t^{SSR}). The theoretical counterpart of Equation (A.4.1) for the nominal-real covariance (φ_{t+1}) is given by the centred form

$$\varphi_{t+1} = \varphi_{t+1}^a + \varphi_{t+1}^b, \tag{A.4.2a}$$

$$\varphi_{t+1}^a = \varphi_0^a + v(\varphi_t^a - \varphi_0^a) + \sigma_w w_{t+1}, \quad w_t \sim iid \quad \mathcal{N}(0, 1), \tag{A.4.2b}$$

$$\varphi_{t+1}^b = \varphi_0^b + v(\varphi_t^b - \varphi_0^b) + b(s_t - \bar{s}), \tag{A.4.2c}$$

where the shadow rate s_t is assumed to be an exogenous state variable with constant volatility σ_s , and the term $\bar{s}$ is the steady state of the shadow rate. Thus, the complete process for the nominal-real covariance is given by

$$\varphi_{t+1} = \varphi_0 + b(s_t - \bar{s}) + v(\varphi_t - \varphi_0) + \sigma_w w_{t+1}, \quad w_t \sim iid \quad \mathcal{N}(0, 1). \tag{A.4.3a}$$

A.4.2 Setup

The exogenous processes for real consumption growth (Δc_{t+1}), inflation (π_{t+1}), and real dividend growth for asset i ($\Delta d_{i,t+1}$) are taken from Boons et al. (2020) (hereafter BDDS2020).

The nominal-real covariance (φ_{t+1}) follows the process discussed above.

$$\pi_{t+1} = \mu_\pi + \rho_\pi(\pi_t - \mu_\pi) + \xi_\pi u_t + \phi_\pi u_{t+1}, \quad (\text{A.4.4a})$$

$$\Delta c_{t+1} = \mu_c + \rho_c(\pi_t - \mu_\pi) + \xi_c \varphi_{t-1} u_t + \sigma_c \eta_{t+1}, \quad (\text{A.4.4b})$$

$$\varphi_{t+1} = \varphi_0 + b(s_t - \bar{s}) + v(\varphi_t - \varphi_0) + \sigma_w w_{t+1}, \quad (\text{A.4.4c})$$

$$\Delta d_{i,t+1} = \mu_i + \rho_i(\pi_t - \mu_\pi) + \xi_i \varphi_{t-1} u_t + \sigma_i \eta_{t+1}, \quad (\text{A.4.4d})$$

$$u_t, \quad \eta_t, \quad w_t \sim iid \quad \mathcal{N}(0, 1). \quad (\text{A.4.4e})$$

Compared with the setup in BDDS2020, Equation (A.4.4c) introduces the role of shadow rate, s_t , to the model.

BDDS2020 specify the representative agent preferences with the Epstein-Zin recursive utility, which yields the log stochastic discount factor (SDF)

$$m_{t+1} = \theta \log \delta - \frac{\theta}{\psi} \Delta c_{t+1} - (1 - \theta) r_{c,t+1}, \quad (\text{A.4.5})$$

where $r_{c,t+1}$ is the log return on the wealth portfolio, that is, the claim on aggregate consumption; $\delta \in (0, 1)$ is the discount rate; ψ is the elasticity of intertemporal substitution (EIS); and $\theta = \frac{1-\gamma}{1-\frac{1}{\psi}}$ with $\gamma > 0$ the coefficient of relative risk aversion.

A.4.3 Coefficients of the wealth-consumption ratio

BDDS2020 conjecture and verify that the log wealth-consumption ratio is linear quadratic in the state variables π_t , φ_t , and u_t . As the main point of departure, the shadow rate enters the process as an additional term

$$\begin{aligned} wc_t = & A_0 + A_1(\pi_t - \mu_\pi) + A_2 \varphi_{t-1} u_t + A_3 u_t + A_4(\varphi_t - \varphi_0) \\ & + A_4^*(s_t - \bar{s}) + A_5(\varphi_t^2 - E[\varphi_t^2]). \end{aligned} \quad (\text{A.4.6})$$

Similarly, the price-dividend ratio for asset i is

$$\begin{aligned} pd_{i,t} = & D_{i,0} + D_{i,1}(\pi_t - \mu_\pi) + D_{i,2} \varphi_{t-1} u_t + D_{i,3} u_t + D_{i,4}(\varphi_t - \varphi_0) \\ & + D_{i,4}^*(s_t - \bar{s}) + D_{i,5}(\varphi_t^2 - E[\varphi_t^2]), \end{aligned} \quad (\text{A.4.7})$$

where $E[\varphi_t^2] = \varphi_t^2 + \frac{\sigma_w^2 + b^2 \sigma_s^2}{1 - v^2}$ is the unconditional mean of φ_t^2 . A Campbell-Shiller approximation gives returns on the aggregate consumption claim (the wealth portfolio), $r_{c,t+1}$, with

approximations constants

$$r_{c,t+1} = \kappa_0 + \kappa_1 wc_{t+1} - wc_t + \Delta c_{t+1}, \quad (\text{A.4.8a})$$

$$\kappa_1 = \frac{e^{E[wc_t]}}{e^{E[wc_t]} + 1}, \quad (\text{A.4.8b})$$

$$\kappa_0 = \log(e^{E[wc_t]} + 1) - \frac{e^{E[wc_t]}}{e^{E[wc_t]} + 1} E[wc_t], \quad (\text{A.4.8c})$$

and returns on any asset i , $r_{i,t+1}$, with approximations constants

$$r_{i,t+1} = \kappa_{i,0} + \kappa_{i,1} pd_{i,t+1} - pd_{i,t} + \Delta pd_{i,t+1}, \quad (\text{A.4.9a})$$

$$\kappa_{i,1} = \frac{e^{E[pd_{i,t}]}}{e^{E[pd_{i,t}]} + 1}, \quad (\text{A.4.9b})$$

$$\kappa_{i,0} = \log(e^{E[pd_{i,t}]} + 1) - \frac{e^{E[pd_{i,t}]}}{e^{E[pd_{i,t}]} + 1} E[pd_{i,t}]. \quad (\text{A.4.9c})$$

The Euler equation for any asset i (including $i = c$) with log-normal returns is

$$0 = E_t[m_{t+1} + r_{i,t+1}] + \frac{1}{2} \text{Var}_t[m_{t+1} + r_{i,t+1}]. \quad (\text{A.4.10})$$

Plug in Equation (A.4.5) and Equation (A.4.8a), and use Equation (A.4.19) (verified later), I get

$$\begin{aligned} m_{t+1} + r_{c,t+1} &= \theta(\log \delta + \kappa_0) + \theta\left(1 - \frac{1}{\psi}\right) \Delta c_{t+1} + \theta(\kappa_1 wc_{t+1} - wc_t) \\ &= \theta(\log \delta + \kappa_0) - \theta wc_t + \theta\left(1 - \frac{1}{\psi}\right) \Delta c_{t+1} + \theta \kappa_1 wc_{t+1}, \end{aligned} \quad (\text{A.4.11})$$

and (corresponding to Equation (OA.63) in BDDS2020)

$$\begin{aligned} \text{Var}_t(m_{t+1} + r_{c,t+1}) &= \text{Var}_t\left(\theta\left(1 - \frac{1}{\psi}\right) \Delta c_{t+1} + \theta \kappa_1 wc_{t+1}\right) \\ &= \theta^2 \left(1 - \frac{1}{\psi}\right)^2 \sigma_c^2 + \theta^2 \kappa_1^2 \text{Var}_t(wc_{t+1}) \\ &\quad + 2\theta^2 \kappa_1^2 \left(1 - \frac{1}{\psi}\right) \text{Cov}_t(\Delta c_{t+1}, wc_{t+1}) \\ &= \theta^2 \left(1 - \frac{1}{\psi}\right)^2 \sigma_c^2 + (\theta \kappa_1)^2 \text{Var}_t(wc_{t+1}). \end{aligned} \quad (\text{A.4.12})$$

Plug Equation (A.4.6), Equation (A.4.11), and Equation (A.4.12) into Equation (A.4.10), and evaluating conditional means and variances, the coefficients A s can be solved in terms

of A_0 by matching the coefficients on the state variables. BDDS2020 show that A_s are all functions of constant parameters and A_0 can be solved numerically.

A.4.4 Coefficients of the price-dividend ratio

Analogous to that for the A_s , but instead of using the Euler equation for $r_{c,t}$, the Euler equation for $r_{i,t}$ is given in Equation (A.4.10). Plug Equation (A.4.5) and Equation (A.4.9a) into Equation (A.4.10), and evaluating conditional means and variances, the coefficients D can be solved in terms of $D_{i,0}$ in closed form, similar to the solution for A_s . BDDS2020 show that D_s are also functions of constant parameters and D_0 can be solved numerically.

A.4.5 Innovations to the stochastic discount factor

To understand the asset pricing implications of the model, Equation (20) of BDDS2020 specify innovations in the SDF as a function of news to contemporaneous consumption growth ($N_{C,t+1}$), news about the future expected path of consumption ($N_{PATH,t+1}$) and news revisions in the future conditional variance of the wealth-consumption ratio ($N_{RISK,t+1}$). Specifically,

$$m_{t+1} - E_t m_{t+1} = -\gamma(E_{t+1} - E_t)\Delta c_{t+1} - (1 - \theta)\kappa_1(E_{t+1} - E_t)w_{c,t+1} \quad (\text{A.4.13a})$$

$$= -\gamma N_{C,t+1} - (1 - \theta)\kappa_1\left(\left(1 - \frac{1}{\psi}\right)N_{PATH,t+1} + \frac{\theta\kappa_1^2}{2}N_{RISK,t+1}\right), \quad (\text{A.4.13b})$$

where they define

$$N_{C,t+1} \equiv (E_{t+1} - E_t)\Delta c_{t+1}, \quad (\text{A.4.14a})$$

$$N_{PATH,t+1} \equiv (E_{t+1} - E_t) \sum_{j=0}^{\infty} \kappa_1^j E_{t+1+j}[\Delta c_{t+2+j}], \quad (\text{A.4.14b})$$

$$N_{RISK,t+1} \equiv (E_{t+1} - E_t) \sum_{j=0}^{\infty} \kappa_1^j \text{Var}_{t+1+j}[w_{c,t+2+j}]. \quad (\text{A.4.14c})$$

To show the above key equations remain valid in this paper's setup, this section derives the related equations that involve the additional term of the shadow rate. First, I compute the innovations for φ_{t+2+j} and φ_{t+2+j}^2 (corresponding to Equation (OA.59) in BDDS2020):

$$\begin{aligned} \varphi_{t+2+j} &= \varphi_0 + b(s_{t+1+j} - \bar{s}) + v(\varphi_{t+1+j} - \varphi_0) + \sigma_w w_{t+2+j}, \\ E_{t+1+j}[\varphi_{t+2+j}] &= \varphi_0 + b(s_{t+1+j} - \bar{s}) + v(\varphi_{t+1+j} - \varphi_0), \\ \varphi_{t+2+j} - E_{t+1+j}[\varphi_{t+2+j}] &= \sigma_w w_{t+2+j}, \end{aligned} \quad (\text{A.4.15})$$

$$\begin{aligned}
\varphi_{t+2+j}^2 &= (\varphi_0 + b(s_{t+1+j} - \bar{s}) + v(\varphi_{t+1+j} - \varphi_0))^2 + \sigma_w^2 w_{t+2+j}^2 \\
&\quad + 2(\varphi_0 + b(s_{t+1+j} - \bar{s}) + v(\varphi_{t+1+j} - \varphi_0))\sigma_w w_{t+2+j}, \\
E_{t+1+j}[\varphi_{t+2+j}^2] &= \varphi_0 + b(s_{t+1+j} - \bar{s}) + v(\varphi_{t+1+j} - \varphi_0) + \sigma_w^2, \\
\varphi_{t+2+j}^2 - E_{t+1+j}[\varphi_{t+2+j}^2] &= \sqrt{2}\sigma_w^2\left(\frac{w_{t+2+j}^2 - 1}{\sqrt{2}}\right), \\
&\quad + 2(\varphi_0 + b(s_{t+1+j} - \bar{s}) + v(\varphi_{t+1+j} - \varphi_0))\sigma_w w_{t+2+j}.
\end{aligned} \tag{A.4.16}$$

Use the above equations, the innovations in wc_{t+2+j} is

$$\begin{aligned}
wc_{t+2+j} &= A_0 + A_1(\pi_{t+2+j} - \mu_\pi) + A_2\varphi_{t+1+j}u_{t+2+j} + A_3u_{t+2+j} \\
&\quad + A_4(\varphi_{t+2+j} - \varphi_0) + A_4^*(s_{t+2+j} - \bar{s}) + A_5(\varphi_{t+2+j}^2 - E[\varphi_t^2]), \\
E_{t+1+j}[wc_{t+2+j}] &= A_0 + A_1(E_{t+1+j}[\pi_{t+2+j}] - \mu_\pi) + A_2E_{t+1+j}[\varphi_{t+1+j}u_{t+2+j}] \\
&\quad + A_3E_{t+1+j}[u_{t+2+j}] + A_4(E_{t+1+j}[\varphi_{t+2+j}] - \varphi_0) \\
&\quad + A_4^*(E_{t+1+j}[s_{t+2+j}] - \bar{s}) + A_5(E_{t+1+j}[\varphi_{t+2+j}^2] - E[\varphi_t^2]), \\
wc_{t+2+j} - E_{t+1+j}[wc_{t+2+j}] &= (A_1\phi_\pi + A_2\varphi_{t+1+j} + A_3)u_{t+2+j} \\
&\quad + (A_4 + 2A_5(\varphi_0 + b(s_{t+1+j} - \bar{s}) + v(\varphi_{t+1+j} - \varphi_0)))\sigma_w w_{t+2+j} \\
&\quad + A_5\sqrt{2}\sigma_w^2\left(\frac{w_{t+2+j}^2 - 1}{\sqrt{2}}\right) + A_4^*(s_{t+2+j} - E_{t+1+j}[s_{t+2+j}]).
\end{aligned} \tag{A.4.17}$$

Corresponding to Equation (OA.61) in BDDS2020, innovations in consumption Δc_{t+2+j} is

$$\Delta c_{t+2+j} - E_{t+1+j}[\Delta c_{t+2+j}] = \sigma_c \eta_{t+2+j}. \tag{A.4.18}$$

Since the shocks u_{t+2+j} , w_{t+2+j} , $\sigma_w^2\left(\frac{w_{t+2+j}^2 - 1}{\sqrt{2}}\right)$ are independent of η_{t+2+j} , and s_{t+2+j} is exogenous and also independent of η_{t+2+j} , Equation (A.4.17) and Equation (A.4.18) imply

$$Cov_{t+1+j}(\Delta c_{t+2+j}, wc_{t+2+j}) = 0. \tag{A.4.19}$$

Equation (A.4.19) is the key to derive Equation (OA.62) in the BDDS2020. Hereafter, the addition of the shadow rate does not affect the derivation of the innovations in the SDF in Equation (A.4.13a).

A.4.6 Price of inflation risk

To identify the price of inflation risk, the BDDS2020 model shows that inflation shocks only affect news to contemporaneous consumption growth ($N_{C,t+1}$), because by Equation (A.4.4b) it is the only shock provided news about expected consumption growth. Indeed, using Equation (A.4.4b), $N_{C,t+1}$ depends only on the shocks η_{t+1} , which corresponding to Equation (OA.68) in BDDS2020

$$-\gamma N_{C,t+1} = -\gamma \sigma_c \eta_{t+1}. \quad (\text{A.4.20})$$

To derive $N_{PATH,t+1}$, I start from iterating Δc_{t+2+j} forward,

$$\begin{aligned} \Delta c_{t+2+q} &= \mu_c + \rho_c(\pi_{t+1+q} - \mu_\pi) + \xi_c \phi_{t+q} u_{t+1+q} + \sigma_c \eta_{t+2+q} \\ &= \mu_c + \rho_c(\rho_\pi(\pi_{t+q} - \mu_\pi) + \xi_\pi u_{t+q} + \phi_\pi u_{t+1+q}) + \xi_q \phi_{t+q} u_{t+1+q} + \sigma_q \eta_{t+2+q} \\ &= \mu_c + \rho_c(\rho_\pi^j(\pi_t - \mu_\pi) + \sum_{q=0}^j \rho_\pi^q(\rho_\pi \phi_\pi + \xi_\pi) u_{t+j-q} - \rho_\pi^j \phi_\pi u_t + \phi_\pi u_{t+1+q}) \\ &\quad + \xi_c(\phi_0 + b^j(s_t - \bar{s}) + v^j(\phi_t - \phi_0) + \sum_{q=0}^j v^q \sigma_w w_{t+j-q}) u_{t+1+q} + \sigma_c \eta_{t+2+q}. \end{aligned} \quad (\text{A.4.21})$$

Applying $(E_{t+1} - E_t)$ to both sides,

$$(E_{t+1} - E_t) \Delta c_{t+2+q} = \rho_c \left(\sum_{q=0}^j \rho_\pi^q (\rho_\pi \phi_\pi + \xi_\pi) u_{t+j-q} + \phi_\pi u_{t+1+q} \right). \quad (\text{A.4.22})$$

Thus, the $N_{PATH,t+1}$ remains consistent with the BDDS2020 model and is given by

$$\begin{aligned} N_{PATH,t+1} &= (E_{t+1} - E_t) \sum_{q=0}^{\infty} \kappa_1^q E_{t+1+q} [\Delta c_{t+2+q}] \\ &= (E_{t+1} - E_t) \Delta c_{t+2} + (E_{t+1} - E_t) \sum_{q=1}^{\infty} \kappa_1^q \Delta c_{t+2+q} \\ &= \xi_c \phi_t u_{t+1} + \sum_{q=1}^j \kappa_1^q \rho_\pi^{q-1} \rho_c (\rho_\pi \phi_\pi + \xi_\pi) u_{t+j-q} + \rho_c \phi_\pi u_{t+1+q} \\ &= \xi_c \phi_t u_{t+1} + \left(\frac{\rho_c \kappa_1 (\rho_\pi \phi_\pi + \xi_\pi)}{1 - \kappa_1 \rho_\pi} + \rho_c \phi_\pi \right) u_{t+1} \\ &= \left(\frac{\rho_c (\phi_\pi + \xi_\pi \kappa_1)}{1 - \kappa_1 \rho_\pi} + \xi_c \phi_t \right) u_{t+1}. \end{aligned} \quad (\text{A.4.23})$$

As the $N_{RISK,t+1}$ depends only on variances and covariances, the BDDS2020 model argues that $N_{RISK,t+1}$ depends only on the shocks w_{t+1} because φ_t is the only source of heteroskedasticity in the model. I insert the shadow rate as an exogenous state variable so that it does not introduce any other source of heteroskedasticity. In other words, $N_{RISK,t+1}$ remains uncorrelated to the shocks η_{t+1} and u_{t+1} (correspond to BDDS2020 Equation (OA.70)).

Thus, with the addition of the shadow rate, I illustrate that the shock η_{t+1} , $u_{\Pi,t+1}$, and w_{t+1} remain driving separate news components of the SDF. Furthermore, the price of inflation risk $\lambda_{u,t}$ is, by definition, the compensation that the representative agent requires to hold one unit of inflation risk ($u_{\Pi,t+1}$). Therefore, the price of the inflation risk, $\lambda_{u,t}$, follows the Equation (23) of BDDS2020:

$$\lambda_{u,t} u_{\Pi,t+1} = \kappa_1 \left(1 - \frac{1}{\psi}\right) N_{PATH,t+1} \quad (\text{A.4.24a})$$

$$= \kappa_1 \left(1 - \frac{1}{\psi}\right) \left(\frac{\rho_c \phi \pi}{1 - \rho_\pi \kappa_1} + \frac{\rho_c \kappa_1 \xi \pi}{1 - \rho_\pi \kappa_1} + \xi_c \varphi_t \right) \frac{u_{\Pi,t+1}}{\phi \pi}. \quad (\text{A.4.24b})$$

A.4.7 Inflation betas

To derive the model-implied inflation beta, news to returns for asset i , $r_{i,t+1}$ is decomposed in a manner similar to the SDF in the BDDS2020 model. I cite and later show that news to returns in Equation (25) of BDDS2020 remains valid with the addition of the shadow rate:

$$(E_{t+1} - E_t) r_{i,t+1} = -\kappa_{i,1} (E_{t+1} - E_t) p d_{i,t+1} - (E_{t+1} - E_t) \Delta d_{i,t+1} \quad (\text{A.4.25a})$$

$$= \kappa_{i,1} (N_{PATH,t+1}^i + N_{m,t+1}^i + \frac{1}{2} N_{RISK,t+1}^i) + N_{D,t+1}^i, \quad (\text{A.4.25b})$$

where

$$N_{PATH,t+1}^i \equiv (E_{t+1} - E_t) \sum_{q=0}^{\infty} \kappa_{i,1}^q E_{t+1+q} [\Delta d_{i,t+2+q}], \quad (\text{A.4.26a})$$

$$N_{m,t+1}^i \equiv (E_{t+1} - E_t) \sum_{q=0}^{\infty} \kappa_{i,1}^q E_{t+1+q} [m_{t+2+q}], \quad (\text{A.4.26b})$$

$$N_{RISK,t+1}^i \equiv (E_{t+1} - E_t) \sum_{q=0}^{\infty} \kappa_{i,1}^q \text{Var}_{t+1+1} [m_{t+2+q} + \kappa_{i,1} p d_{i,t+1} + \Delta d_{i,t+1}], \quad (\text{A.4.26c})$$

$$N_{D,t+1}^i \equiv (E_{t+1} - E_t) \Delta d_{i,t+1}. \quad (\text{A.4.26d})$$

Then, the BDDS2020 model shows that inflation shocks only affect $N_{PATH,t+1}^i$ and $N_{m,t+1}^i$. In other words, $N_{RISK,t+1}^i$ and $N_{D,t+1}^i$ are uncorrelated to inflation shocks $u_{\Pi,t+1}$, so they do not contribute to inflation beta. In this paper's setup, even with the shadow rate, it remains

true that only $N_{PATH,t+1}^i$ and $N_{m,t+1}^i$ depends on inflation shocks. To verify this, I derive and summarise the shocks driving $N_{PATH,t+1}^i$, $N_{m,t+1}^i$, $N_{RISK,t+1}^i$ and $N_{D,t+1}^i$ in reference to BDDS2020.

Iterating $\Delta d_{i,t+2+q}$ forward,

$$\begin{aligned}
\Delta d_{i,t+2+q} &= \mu_i + \rho_i(\pi_{t+1+q} - \mu_\pi) + \xi_i \varphi_{t+q} u_{t+1+q} + \sigma_i \eta_{t+2+q} \\
&= \mu_i + \rho_i(\rho_\pi(\pi_{t+q} - \mu_\pi) + \xi_\pi u_{t+q} + \phi_\pi u_{t+1+q}) + \xi_i \varphi_{t+q} u_{t+1+q} + \sigma_i \eta_{t+2+q} \\
&= \mu_i + \rho_i(\rho_\pi^j(\pi_t - \mu_\pi) + \sum_{q=0}^j \rho_\pi^q(\rho_\pi \phi_\pi + \xi_\pi) u_{t+j-q} - \rho_\pi^j \phi_\pi u_t + \phi_\pi u_{t+1+q}) \\
&\quad + \xi_i(\varphi_0 + b^j(s_t - \bar{s}) + v^j(\varphi_t - \varphi_0) + \sum_{q=0}^j v^q \sigma_w w_{t+j-q}) u_{t+1+q} + \sigma_i \eta_{t+2+q}.
\end{aligned} \tag{A.4.27}$$

Applying $(E_{t+1} - E_t)$ to both sides,

$$(E_{t+1} - E_t) \Delta d_{i,t+2+q} = \rho_i \left(\sum_{q=0}^j \rho_\pi^q (\rho_\pi \phi_\pi + \xi_\pi) u_{t+j-q} + \phi_\pi u_{t+1+q} \right). \tag{A.4.28}$$

Thus, the $N_{PATH,t+1}^i$ remains consistent with the BDDS2020 model and is given by

$$\begin{aligned}
N_{PATH,t+1}^i &= (E_{t+1} - E_t) \sum_{q=0}^{\infty} \kappa_{i,1}^q E_{t+1+q} [\Delta d_{i,t+2+q}] \\
&= (E_{t+1} - E_t) \Delta d_{i,t+2} + (E_{t+1} - E_t) \sum_{q=1}^{\infty} \kappa_{i,1}^q \Delta d_{i,t+2+q} \\
&= \xi_i \varphi_t u_{t+1} + \sum_{q=1}^j \kappa_{i,1}^q \rho_\pi^{q-1} \rho_i (\rho_\pi \phi_\pi + \xi_\pi) u_{t+j-q} + \rho_i \phi_\pi u_{t+1+q} \\
&= \xi_i \varphi_t u_{t+1} + \left(\frac{\rho_i \kappa_{i,1} (\rho_\pi \phi_\pi + \xi_\pi)}{1 - \kappa_{i,1} \rho_\pi} + \rho_i \phi_\pi \right) u_{t+1} \\
&= \left(\frac{\rho_i (\phi_\pi + \xi_\pi \kappa_{i,1})}{1 - \kappa_{i,1} \rho_\pi} + \xi_i \varphi_t \right) u_{t+1}.
\end{aligned} \tag{A.4.29}$$

Recall Equation (OA.79) in BDDS2020 regarding $N_{m,t+1}^i$, the shadow rate indeed introduces an extra term to the equation

$$\begin{aligned}
N_{m,t+1}^i = & -\frac{\rho_c}{\psi} \frac{\kappa_{i,1}(\rho\pi\phi\pi + \xi\pi)}{1 - \kappa_{i,1}\rho\pi} u_{t+1} \\
& + ((\theta - 1)(\kappa_1 A_1 \xi\pi - A_3) - \frac{\rho_c}{\psi} \psi\pi - \frac{1}{\psi} \xi_c \phi_t) u_{t+1} \\
& + (E_{t+1} - E_t) \sum_{q=0}^{\infty} \kappa_{i,1}^q [-(\theta - 1)A_4(\phi_{t+1+j} - \phi_0) - (\theta - 1)A_4^*(s_{t+1+j} - \bar{s}) \\
& - (\theta - 1)A_5(\phi_{t+1+j}^2 - E[\phi_t^2])] \\
& + (E_{t+1} - E_t) \sum_{q=0}^{\infty} \kappa_{i,1}^q [(\theta - 1)\kappa_1 A_4(E_{t+1+j}\phi_{t+2+j} - \phi_0) \\
& + (\theta - 1)\kappa_1 A_4^*(E_{t+1+j}s_{t+2+j} - \bar{s}) \\
& + (\theta - 1)\kappa_1 A_5(E_{t+1+j}\phi_{t+2+j}^2 - E[\phi_t^2])].
\end{aligned} \tag{A.4.30}$$

Under the assumption that s_{t+2+j} is exogenous, and that the innovations $(E_{t+1} - E_t)\phi_{t+2+j}$ and $(E_{t+1} - E_t)\phi_{t+2+j}^2$ only depends on the shock w_{t+1} , the process for $N_{m,t+1}^i$ remains (correspond to Equation (OA.80) in BDDS2020)

$$\begin{aligned}
N_{m,t+1}^i = & -\frac{\rho_c}{\psi} \frac{\kappa_{i,1}(\rho\pi\phi\pi + \xi\pi)}{1 - \kappa_{i,1}\rho\pi} u_{t+1} \\
& + ((\theta - 1)(\kappa_1 A_1 \xi\pi - A_3) - \frac{\rho_c}{\psi} \psi\pi - \frac{1}{\psi} \xi_c \phi_t) u_{t+1} \\
& + F(w_{t+1}),
\end{aligned} \tag{A.4.31}$$

where $F(\cdot)$ is a function of w_{t+1} but not of (η_{t+1}, u_{t+1}) . The shadow rate inclusion does not affect Equation (81) in BDDS2020

$$\begin{aligned}
N_{D,t+1}^i & \equiv (E_{t+1} - E_t)\Delta d_{i,t+1} \\
& = \sigma_i \eta_{t+1},
\end{aligned} \tag{A.4.32}$$

where $N_{D,t+1}^i$ depends only on the shocks η_{t+1} . Finally, BDDS2020 shows that $N_{RISK,t+1}^i$ depends only on variances and covariance. With the addition of shadow rate, ϕ_t remains the only source of heteroskedasticity in the model, $N_{RISK,t+1}^i$ depends only on the shocks w_{t+1} .

A.5 Robustness and additional results

This section contains robustness and additional results.

Table A.1 Descriptive statistics.

	Mean	Median	Std Dev	Sharpe	Max	Min	Pos	Neg	Obs
Australia	13.01	13.90	22.10	0.59	17.99	-44.51	248	163	414
Austria	11.09	13.14	26.23	0.42	28.11	-37.04	237	174	414
Belgium	13.11	18.15	20.89	0.63	26.76	-36.56	251	160	414
Canada	10.23	12.86	18.60	0.55	21.26	-26.94	249	162	414
Denmark	14.28	18.72	19.67	0.73	21.30	-25.67	249	162	414
Finland	12.52	7.57	29.38	0.43	33.26	-31.76	204	174	381
France	12.58	13.36	20.82	0.60	21.03	-22.41	245	166	414
Germany	12.05	14.58	22.65	0.53	23.69	-24.35	242	169	414
Greece	11.17	5.82	38.01	0.29	55.31	-36.70	174	133	310
Hong Kong	14.94	12.31	25.23	0.59	33.23	-43.44	252	159	414
Ireland	6.51	11.44	21.68	0.30	19.22	-26.04	211	167	381
Italy	10.38	10.10	24.93	0.42	30.99	-23.60	228	183	414
Japan	7.36	6.72	20.64	0.36	24.26	-19.38	222	189	414
Netherlands	12.88	15.58	18.61	0.69	14.39	-25.11	260	151	414
New Zealand	9.09	10.77	22.13	0.41	27.65	-22.44	211	167	381
Norway	12.58	15.09	25.61	0.49	21.47	-33.36	234	177	414
Portugal	4.71	3.09	22.43	0.21	28.41	-26.25	200	178	381
Singapore	10.81	10.79	24.86	0.43	25.84	-41.34	241	170	414
Spain	13.60	14.60	24.28	0.56	26.72	-25.27	233	178	414
Sweden	15.30	15.96	24.34	0.63	25.49	-26.66	238	173	414
Switzerland	13.46	14.40	17.14	0.79	16.68	-17.64	248	163	414
UK	10.17	9.59	17.36	0.59	15.11	-21.53	240	171	414
USA	11.61	15.89	14.84	0.78	13.28	-21.22	270	141	414
Brazil	16.46	17.49	37.04	0.44	36.78	-37.63	169	133	303
Czech Republic	12.08	15.41	26.85	0.45	30.08	-29.44	172	124	297
Egypt	16.35	6.49	32.27	0.51	42.71	-33.52	160	136	297
Hungary	16.18	15.05	34.96	0.46	46.17	-43.35	166	130	297
India	12.06	9.42	28.53	0.42	36.68	-28.48	172	147	321
Indonesia	18.81	13.01	45.73	0.41	94.41	-40.54	213	165	381
Israel	10.44	18.07	24.76	0.42	26.90	-18.85	128	79	209
Korea	11.89	4.01	34.62	0.34	70.60	-31.26	198	180	381
Malaysia	9.73	8.86	26.44	0.37	50.05	-30.20	212	166	381
Mexico	18.52	20.10	29.83	0.62	43.77	-34.25	226	152	381
Philippines	11.35	9.72	28.91	0.39	43.39	-29.22	211	167	381
Poland	17.29	12.11	41.16	0.42	90.59	-34.82	175	144	321
Russia	22.53	21.61	48.58	0.46	61.13	-60.57	163	133	297
Taiwan	11.84	11.30	32.83	0.36	46.44	-33.67	207	171	381
Thailand	13.94	15.84	34.48	0.40	43.23	-34.01	219	159	381
World	8.63	13.25	14.76	0.58	11.90	-19.79	236	142	381

This table presents the descriptive statistics in annualised percentages for the MSCI Equity USD Total Return Index. The full sample is from March 1985 to September 2019.

Table A.2 Correlation with lagged inflation.

	$cor(\pi_t, \pi_{t-1})$	$cor(\Delta c_t^N, \pi_{t-1})$	$cor(\Delta c_t, \pi_{t-1})$
Panel A: Full sample			
G7	0.79	0.63	-0.08
OECD	0.89	0.54	0.00
USA	0.60	0.48	-0.11
Panel B: Pre 2009			
G7	0.78	0.54	-0.25
OECD	0.89	0.45	-0.16
USA	0.61	0.39	-0.25
Panel C: Post 2009			
G7	0.50	0.56	0.19
OECD	0.47	0.51	0.29
USA	0.04	0.39	0.22

This table presents the auto-correlation of inflation (π_t), the correlation between nominal consumption growth (Δc_t^N) and lagged inflation, and the correlation between real consumption growth (Δc_t) and lagged inflation for G7, OECD and USA area. The US quarterly per capita nominal and real consumption growth use data from the National Income and Product Accounts Tables and the inflation uses data from the Bureau of Labor Statistics. The G7 universe and OECD universe aggregate use OECD data. All variables are in log terms. The sample period is from June 1970 to September 2019 in Panel A, and Panel B and C split the full sample around December 2008.

Table A.3 Country composition of inflation beta-sorted portfolios.

	Rank1	Rank2	Rank3	Rank4	Rank5
Panel A: 02/1995-03/2009					
P1	Belgium (0.59)	Singapore (0.52)	Switzerland (0.49)	Indonesia (0.47)	Greece (0.44)
P2	India (0.42)	Mexico (0.35)	Russia (0.32)	Taiwan (0.32)	Italy (0.31)
P3	Korea (0.44)	Israel (0.42)	Mexico (0.39)	Norway (0.35)	Russia (0.34)
P4	Sweden (0.45)	Czech Republic (0.39)	Finland (0.38)	Israel (0.35)	Poland (0.32)
P5	Hong Kong (0.75)	UK (0.67)	Ireland (0.61)	Canada (0.54)	Australia (0.52)
Panel B: 03/2009-09/2019					
P1	Indonesia (0.99)	India (0.87)	Philippines (0.83)	Singapore (0.82)	Thailand (0.63)
P2	Taiwan (0.78)	Korea (0.69)	Belgium (0.55)	Ireland (0.54)	Egypt (0.51)
P3	Sweden (0.87)	Finland (0.66)	Denmark (0.61)	Mexico (0.57)	Canada (0.56)
P4	Germany (0.90)	Portugal (0.67)	UK (0.63)	Italy (0.53)	USA (0.47)
P5	Spain (1.00)	Israel (1.00)	Poland (0.92)	Switzerland (0.88)	Czech Republic (0.87)

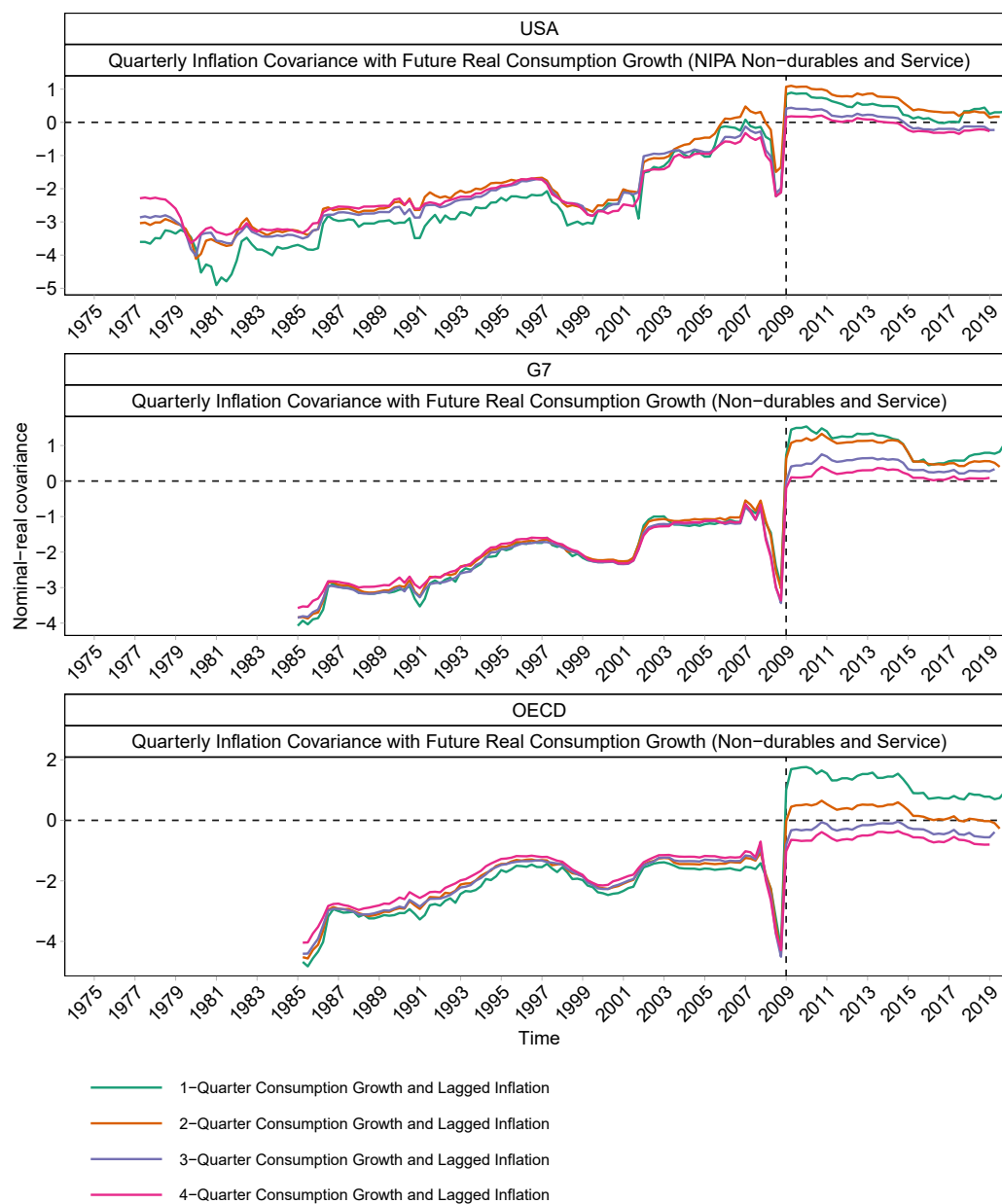
This table reports the country composition of inflation beta-sorted portfolios. We report the top five country equity indices (with the frequency in parentheses) entering each portfolio. The portfolios are re-balanced monthly. The sample period is between 02/1995-03/2009 for Panel A and 03/2009-09/2019 for Panel B.

Table A.4 Average weights of inflation beta rank-weighted portfolios.

02/1995-03/2009		03/2009-09/2019	
Country	Average weight	Country	Average weight
Indonesia	-0.05	Indonesia	-0.10
Switzerland	-0.05	Philippines	-0.09
Malaysia	-0.04	Singapore	-0.08
Singapore	-0.04	India	-0.08
Taiwan	-0.04	Belgium	-0.07
Greece	-0.04	Thailand	-0.07
Belgium	-0.04	Korea	-0.06
Portugal	-0.03	Ireland	-0.06
New Zealand	-0.03	New Zealand	-0.05
Spain	-0.02	Taiwan	-0.05
Egypt	-0.02	Egypt	-0.04
India	-0.02	Malaysia	-0.03
Korea	-0.02	Brazil	-0.03
Philippines	-0.02	Greece	-0.03
Russia	-0.01	Canada	-0.02
Brazil	-0.01	Hong Kong	-0.02
Italy	-0.01	Mexico	-0.01
Norway	-0.01	Norway	0.00
Finland	-0.01	Australia	0.00
France	-0.01	Sweden	0.01
Mexico	0.00	Austria	0.01
Thailand	0.00	Netherlands	0.01
Israel	0.01	Finland	0.02
Denmark	0.01	Denmark	0.02
Poland	0.02	Russia	0.02
USA	0.02	USA	0.03
Sweden	0.02	Germany	0.04
Hungary	0.02	Japan	0.05
Czech Republic	0.03	Italy	0.06
Germany	0.03	UK	0.06
Canada	0.03	France	0.06
Austria	0.04	Hungary	0.06
Australia	0.04	Portugal	0.06
Japan	0.04	Czech Republic	0.08
UK	0.05	Israel	0.08
Netherlands	0.05	Switzerland	0.08
Ireland	0.06	Poland	0.09
Hong Kong	0.06	Spain	0.10

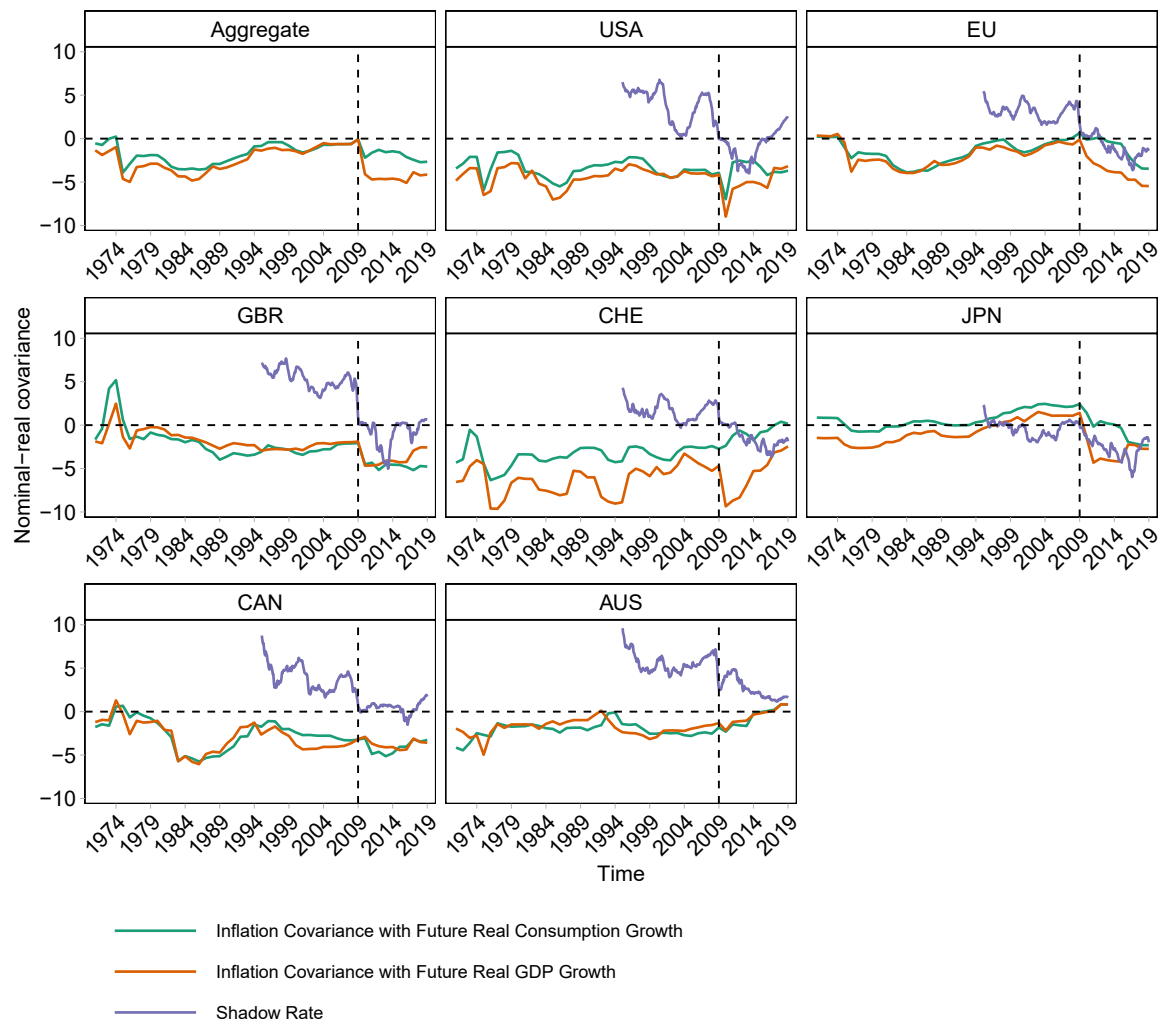
This table reports the mean of rank portfolio weights for the inflation beta-sorted portfolios.

Fig. A.7 Alternative measures of the nominal-real covariance with different horizons.



Each of the measures includes the coefficients on rolling regressions of 1-quarter to 4-quarter consumption growth on lagged inflation, respectively. The US quarterly per capita real consumption growth uses data from the NIPA Tables. The G7 universe and OECD universe aggregate use OECD data. The quarterly real consumption growth uses consumption expenditures on nondurables and services.

Fig. A.8 Nominal-real covariance and the shadow short rate around the world.



The evolution of nominal-real covariance and the shadow short rate around the world. This figure presents the LJK shadow short rate (in monthly and per cent unit) for the major central bank around the world. The nominal-real covariance is estimated using JST annual data on real consumption (GDP) growth and one-year lagged inflation.

Fig. A.9 Inflation risk premium portfolios.



The figure shows the time series plot of the cumulative excess return of inflation beta-sorted portfolios. The excess returns are ex-post adjusted to volatility at 10% annualised. The sample period is from Feb 1995 to Sep 2019.

Appendix B

B.1 Monetary policy transmission mechanism

In order to create policy exposure indices, we interact policy policy-related variables with currency characteristics that are linked to monetary policy sensitivity of currency exchange rate in the previous literature. In this section, we propose the following currency characteristics that are linked to monetary policy transmission mechanisms and policy sensitivity of exchange rates.

Net foreign asset We expect the currency of countries with a higher level of external liabilities to be more exposed to US monetary policy. Intuitively, with debt contracts denominated in the US dollar, contractionary US monetary policy which leads to an appreciation of the US dollar results in the dollar debt burden of debtor countries increasing. Since their assets are typically denominated in domestic currency and so do not increase in value, there is a resulting deterioration in the country's balance sheet (Mishkin, 2014).

In Gabaix and Maggiori (2015), the model predicts that exchange rates are jointly determined by global imbalance and financiers' risk-bearing capacity. In their set-up, a financial disruption, by reducing financiers' risk-bearing capacity, generates an immediate currency depreciation and an expectation of future appreciation to incentives financiers to sustain the imbalance. Empirically, Della Corte et al. (2016) show that net debtor countries need to offer a currency risk premium to compensate investors who are willing to finance negative external imbalances as their currencies tend to depreciate in bad times. Thus, net borrower countries are expected to be more sensitive (depreciated more) to tightening US policy shocks compared to net lenders.

Global trade centrality We expect the currency of the central country, who has strong trade linkages with countries that are important for the output of tradable goods, to be less sensitive to the US monetary policy surprise. Richmond (2019)'s model on trade network

proposed that central countries will be more exposed to common global risk, and thus their currencies are a good hedge against global consumption risk.

Countries' differential exposure to global shocks leads to variation in their real exchange rates (RERs), where RERs are simply the relative price of countries' consumption bundles.¹ Therefore, when a country experiences a bad shock, the price of its consumption bundle will increase relative to a country that experienced a less severe shock. For example, if the U.S. receives a negative consumption shock that increases the price of its consumption basket relative to Mexico's, the dollar will appreciate relative to the peso.

As a result, central (peripheral) countries' currencies appreciate in high (low) marginal utility states so that they are a good hedge against global consumption risk. This results in central countries having low interest rates and currency risk premia, indicating that central country currencies are less sensitive to the US monetary policy surprise.

Interest rate differentials Currency carry may capture the monetary policy sensitivity of a currency in multiple ways. For example, carry is a strong predictor of currency excess returns (Lustig et al., 2011). A US investor loads up on global risk by investing in high interest rate currencies and borrowing in low interest rate currencies. On the other hand, Mueller et al. (2017) illustrate a theoretical model and show that a rise in monetary policy uncertainty in the US increases the foreign currency's expected excess return. This increase in excess return in response to higher monetary policy uncertainty is larger for currencies with higher interest rates. In other words, we expect currencies with higher interest rates to be more sensitive to monetary policy.

Inflation differentials Engel et al. (2022) find evidence that year-on-year inflation rate differentials consistently predict currency excess returns while the relationship between interest rates and currency excess returns is not stable over time. The paper estimates the "Fama Puzzle" regression with the year-on-year inflation differentials and found a consistent negative relationship between excess return and inflation differentials. They propose that the inflation differentials are a stronger measure of monetary policy stance and a better predictor of excess returns than the interest rate differential, even prior to the financial crisis. Thus, currency inflation differentials may pick up the policy sensitivity of a currency in a mechanism similar to interest rate differential.

¹The definition of RER here is such that a lower RER means a stronger dollar and, consequently, a lower valuation level of the foreign currency.

Equity beta Another useful measure of currency risk in the post-crisis period is the conditional equity beta. Lilley and Rinaldi (2020) suggest that, in the period prior to the crisis, central banks of the riskier currencies (e.g. AUD and NZD) were found to hike policy rates most aggressively when risk premia increased (US equity price decline), which means the goal of exchange rate smoothing take precedence than easing monetary condition. However, the responsiveness of interest rate spread to risk premia decreased largely after the crisis. Thus, exchange rates are adjusted to compensate investors through expected appreciation when risk premia increases, which leads to an increase in the conditional equity beta. Without movement in interest rate spread, riskier currencies that have high equity beta would be more sensitive to US monetary policy.

B.2 Data

B.2.1 Currency returns

High-frequency currency spot returns We focus on the commonly traded currencies for the following countries or areas: Australia, Brazil, Canada, Switzerland, Czech Republic, Euro Area, United Kingdom, Hungary, Japan, Mexico, Norway, New Zealand, Sweden, Singapore, South Africa, and Poland.

For each of the aforementioned currencies, we collect tick-by-tick high-frequency spot rate data from Tick History. Our measure of the currency response to policy shocks is the change in the spot rate between 10 minutes before and 20 minutes after the announcement. The spot rate change is in percentage.

Daily currency excess returns The data for daily spot exchange rates and one-, three-, and six-month forward exchange rates cover the same sample period as above and are mainly obtained from JPMorgan Data Query, where missing data are appropriately filled with data from Bloomberg and WMR Reuters via DataStream.

At any pricing date t , we can buy a forward with maturity on the next IMM date that is further than 14 calendar days in the future. We choose to roll two weeks before the IMM date to simulate what is actually done on average. Then, the daily excess returns earned from trading day t to trading day $t + 1$ can be calculated from the ratio of the nearest IMM-dated forward price on the trading day $t + 1$ to the same nearest IMM-dated forward price on the trading day t , except the roll-day. Mathematically,

$$R_{t,t+1} = \frac{F_{t+1}^{m-1}}{F_t^m} \quad (\text{B.2.1})$$

where the superscript denotes the number of days to the nearest IMM-dated maturity, F_t^m denotes the IMM-dated forward price on the day t , F_{t+1}^{m-1} denotes the price of the same IMM-dated forward contract on the day $t + 1$ (with one less day to maturity). Also, we must form roll-day returns from the ratio of the nearest IMM-dated price on the roll day to the second-nearest IMM-dated price of the previous pricing date.

Hence, we must model the returns from IMM-dated forwards with respect to these IMM-dated maturities. However, our data is for fixed maturity, meaning that, for each pricing date, the forward settlement date is different (market conventions are all applied²). To estimate the returns derived from the contract we hold, we must interpolate between the fixed maturities. We perform simple linear interpolation on the forward prices to arrive at IMM-dated forward prices.

B.2.2 Currency characteristics

The currency-level characteristics we discuss in the paper include the NFA-to-GDP ratio, trade centrality, interest rate differential, inflation differential, and equity beta.

The NFA/GDP ratio is an updated version of the Lane and Milesi-Ferretti (2018) dataset kindly provided by Gian Maria Milesi-Ferretti. For the Euro Area, we use the average of core euro countries: Austria, Belgium, Finland, France, Germany, and the Netherlands.

We splice the trade network centrality data of Richmond (2019), available on Robert Richmond's website until 2016³ with our updated data to 2019. Our updated data follows the original methodology and uses bilateral trade data from the International Monetary Fund's Direction of Trade Statistics. GDP data in US dollars are from the World Bank's World Development Indicators.

For each currency, we collect from Bloomberg a mixture of -IBOR rates, swap rates on interbank deposits, and implied yields to supply the daily interest rate data. Table B.1 lists

²We compute one, three, and six-month maturities by first calculating the spot settlement dates, adding the appropriate number of months to the date, keeping the day of the month the same, unless this would exceed the number of days in the month, in which case it is set to the last day of the month. If the forward settlement date lands on a weekend or a holiday, then it is advanced to the following business day. If, in advancing the date we would be in the next month, then instead we adjust the date to the last date in the month that is a business day. If the spot settlement falls on the last business day of the month, then the forward settlement date must also lie on the last business day of the month.

³<https://robertjrichmond.com/Data.html>.

the Bloomberg tickers. We interpolate the daily interest rate data to fill missing data and use a 20-day moving average to deal with outliers. For the euro area, we use the interest rate of Germany before 1999.

We estimate trend CPI inflation differentials by relying on a measure of trend inflation proposed by Cieslak and Povala (2015) and calculated for different countries using CPI indexes from the International Monetary Fund's IFS. Specifically,

$$\tau_t^{CPI} = (1 - v) \sum_{i=0}^{t-1} v^i \pi_{t-i} \quad (\text{B.2.2})$$

where $\pi_t = \ln \frac{CPI_t}{CPI_{t-1}}$ is the year-over-year inflation at monthly sampling. We calibrate the v parameter to be 0.987. In the early sample, if there is any year-over-year inflation above 10% we just use the actual year-over-year inflation and we only switch to the moving average as it goes below 10% (and we initialise at 10% in this case). We never go back to the actual inflation in the later period even if it goes above 10%.

We construct the monthly US equity beta for each currency similarly to Lilley and Rinaldi (2020). To make sure that the conditional equity beta captures long-term currency characteristics, at the end of every month, we regress the daily log appreciation of each currency on the daily log return of the S&P 500 futures using rolling five-year windows. The futures data are sampled at daily close of the stock market in New York.

B.3 Additional tables and figures

This section contains additional tables and figures.

Table B.1 Bloomberg tickers.

Currency	Ticker
AUD	ADBB3M Curncy
BRL	PREDI90 Index
CAD	CDOR03 Index
CHF	SF0003M Index
CZK	PRIB03M Index
DEM	FD0003M Index
EUR	EUR003M Index
GBP	BP0003M Index
HUF	BUBOR03M Index
JPY	JY0003M Index
MXN	MPSWC Curncy
NOK	NIBOR3M Index
NZD	NDBB3M Curncy
PLN	WIBO3M Index
SEK	STIB3M Index
SGD	SORF3M Index
USD	US0003M Index
ZAR	JIBA3M Index

This table reports the Bloomberg tickers used to calculate interest rate differentials. The tickers of type ‘xxxx3M Curncy’ are implied yields, the ‘Index’ tickers are -IBOR rates, and all others are swaps on interbank rates.

Table B.2 Descriptive statistics.

				Percentiles				
	Frequency	Mean	SD	5th	25th	50th	75th	95th
Panel A: sample period 03/1995-12/2008								
NFA/GDP	Annual	-0.03	0.69	-0.81	-0.42	-0.17	0.13	1.63
Trade Centrality	Annual	0.43	0.26	0.12	0.23	0.34	0.62	0.93
Interest Rate Diff	Daily	3.02	6.08	-3.53	-0.98	0.90	6.27	16.01
Inflation Diff	Monthly	2.24	4.33	-2.19	-0.65	0.09	4.94	11.09
Equity Beta	Monthly	-0.01	0.08	-0.13	-0.07	-0.01	0.04	0.15
Spot Return	Intraday	0.04	0.15	-0.20	-0.05	0.04	0.12	0.28
Panel B: sample period 03/1995-03/2019								
NFA/GDP	Annual	0.01	0.75	-0.79	-0.46	-0.17	0.21	1.75
Trade Centrality	Annual	0.45	0.25	0.13	0.25	0.38	0.64	0.91
Interest Rate Diff	Daily	2.48	4.73	-2.38	-0.68	0.91	4.72	12.77
Inflation Diff	Monthly	1.60	3.32	-2.09	-0.55	0.13	3.69	8.21
Equity Beta	Monthly	0.09	0.12	-0.13	0.02	0.09	0.16	0.27
Spot Return	Intraday	0.03	0.15	-0.21	-0.06	0.03	0.12	0.29

This table reports descriptive statistics for variables used in estimating monetary policy exposure. Column 1 reports the frequency of variables. In Panel A and B, Column 2 and 3 reports the time-series average of cross-sectional averages and standard deviation for the six variables. The rest of the columns report the time-series average of cross-sectional percentiles. The sample period is between 03/1995-12/2008 for Panel A, and 03/1995-03/2019 for Panel B.

Table B.3 Shocks correlation matrix.

	SP500	Rate Changes	MP Shocks	Info Shocks
Panel A: 03/1995-12/2008				
SP500	1.00			
Rate Changes	-0.46	1.00		
MP Shocks	-0.85	0.86	1.00	
Info Shocks	0.52	0.51	0.01	1.00
Panel B: 03/1995-03/2019				
SP500	1.00			
Rate Changes	-0.42	1.00		
MP Shocks	-0.80	0.86	1.00	
Info Shocks	0.49	0.52	0.00	1.00

This table reports the correlation matrix among measures of monetary policy-related variables. The sample period is between 03/1995-12/2008 for Panel A, and 03/1995-03/2019 for Panel B.

Table B.4 Currency characteristics correlation matrix.

	NFA/GDP	Trade Centrality	Interest Rate Diff	Inflation Diff	Equity Beta
Panel A: sample period 03/1995-12/2008					
NFA/GDP	1.00				
Trade Centrality	0.77	1.00			
Interest Rate Diff	-0.50	-0.74	1.00		
Inflation Diff	-0.86	-0.96	0.66	1.00	
Equity Beta	0.20	0.60	-0.13	-0.53	1.00
Panel A: sample period 03/1995-03/2019					
NFA/GDP	1.00				
Trade Centrality	0.58	1.00			
Interest Rate Diff	-0.63	-0.70	1.00		
Inflation Diff	-0.63	-0.93	0.68	1.00	
Equity Beta	0.35	0.68	-0.28	-0.68	1.00

This table reports the correlation matrix among cross-sectional averaged currency characteristics. The sample period is between 03/1995-12/2008 for Panel A, and 03/1995-03/2019 for Panel B.

Table B.5 Estimated country-specific responsiveness (pre-2009).

Country	Panel A: Average Responsiveness			Panel B: Average Characteristics				
	Rate Changes	MP Shocks	Info Shocks	NFA/GDP	Trade Centrality	Interest Rate Diff	Inflation Diff	Equity Beta
Australia	-5.30 (1.21)	-7.33 (1.87)	1.53 (2.74)	-0.53	0.31	1.50	0.35	0.02
New Zealand	-4.53 (1.13)	-6.29 (1.75)	1.49 (2.56)	-0.78	0.10	2.71	0.13	0.03
Norway	-4.19 (1.22)	-5.06 (1.88)	-0.95 (2.26)	0.35	0.27	0.79	-0.09	-0.08
Sweden	-4.08 (1.07)	-5.22 (1.62)	-0.08 (2.32)	-0.24	0.38	-0.39	-0.27	-0.05
Euro Area	-3.83 (0.96)	-4.55 (1.44)	-1.11 (2.02)	-0.11	0.71	-0.81	-0.69	-0.10
Hungary	-3.70 (1.04)	-4.87 (1.44)	0.24 (2.71)	-0.77	0.22	7.56	11.34	-0.03
Brazil	-3.58 (1.14)	-6.28 (1.44)	4.97 (1.63)	-0.34	0.19	15.96	5.66	0.14
Czech Republic	-3.37 (0.95)	-4.42 (1.32)	0.09 (1.77)	-0.17	0.24	1.90	4.13	-0.03
Switzerland	-3.29 (0.94)	-3.54 (1.27)	-2.13 (1.61)	1.11	0.47	-2.47	-1.35	-0.14
South Africa	-3.27 (0.83)	-4.82 (1.00)	1.96 (1.40)	-0.18	0.18	7.22	5.26	0.05
Poland	-3.25 (1.15)	-4.70 (1.51)	1.50 (1.42)	-0.37	0.27	7.35	6.11	0.01
United Kingdom	-3.21 (0.87)	-3.89 (1.29)	-0.67 (1.52)	-0.03	0.86	1.27	-0.05	-0.06
Canada	-2.80 (0.65)	-4.28 (0.87)	1.91 (1.19)	-0.16	0.65	-0.29	-0.44	0.05
Japan	-2.42 (0.77)	-2.08 (1.01)	-2.96 (1.10)	0.32	0.62	-3.82	-2.48	-0.06
Mexico	-1.70 (0.53)	-3.30 (0.56)	3.22 (0.85)	-0.37	0.44	10.40	9.95	0.11
Singapore	-0.59 (0.21)	-1.01 (0.24)	0.71 (0.50)	1.92	0.95	-1.73	-1.49	0.00

This table reports the country's average response to different monetary policy-related variables and average country characteristics. Panel A reports the θ_i for each country estimated from the individual univariate regression $r_{i,t} = \theta_i \text{Shocks}_t + \varepsilon_{it}$, where i is the currency identifier, t is the date of the scheduled FOMC meeting, and r_{it} is the intraday currency spot return in the 30-minute window surrounding the FOMC press releases. Shocks_t is one of the structural shocks or innovations of interest: (1) policy rate changes, (2) purged policy shocks, and (3) central bank information shocks, respectively. A positive surprise/shock is tightening. We report Newey-West standard errors with optimal lags in parentheses. Panel B reports country-specific time-series averages for the five characteristic variables. The sample period is 01/1996-12/2008.

Table B.6 Currency portfolio return correlation matrix.

	02/1996-12/2008					01/2009-07/2019				
	Rate	MP	Info	Mix	Carry	Rate	MP	Info	Mix	Carry
Panel A: L/S Portfolios										
Rate	1.00					1.00				
MP	0.52	1.00				0.89	1.00			
Info	-0.06	0.65	1.00			0.50	0.65	1.00		
Mix	0.24	0.90	0.91	1.00		0.77	0.91	0.91	1.00	
Carry	0.13	0.71	0.84	0.86	1.00	0.41	0.59	0.83	0.78	1.00
Dollar	0.52	0.43	0.03	0.24	0.14	0.63	0.65	0.50	0.64	0.53
Panel B: Rank-Weighted Portfolios										
Rate	1.00					1.00				
MP	0.66	1.00				0.93	1.00			
Info	-0.08	0.60	1.00			0.62	0.80	1.00		
Mix	0.33	0.89	0.89	1.00		0.82	0.95	0.95	1.00	
Carry	0.10	0.68	0.86	0.86	1.00	0.49	0.69	0.86	0.81	1.00
Dollar	0.55	0.48	-0.01	0.26	0.14	0.65	0.71	0.53	0.65	0.53

This table reports return correlation among currency portfolios based on exposures to different monetary policy-related variables and currency risk factors. We report results for the long-short portfolios constructed by sorting currencies into five bins based on the cross-section of signals in Panel A, and the corresponding rank-weighted portfolio in Panel B. Signals are foreign currency's exposures to (1) policy rate changes (Rate), (2) pure monetary policy shocks (MP), (3) central bank information shocks (Info). We also report results for inverse volatility weighted portfolios of MP and Info, as well as the carry trade strategy. The sample period is between 03/1995-12/2008 for in-sample and 03/1995-07/2019 for out-of-sample.

Table B.7 Currency composition: carry trade and monetary policy exposure portfolios.

	07/1996-12/2008					01/2009-07/2019				
	Rank1	Rank2	Rank3	Rank4	Rank5	Rank1	Rank2	Rank3	Rank4	Rank5
Panel A: Rate Changes Exposure Portfolios										
P1	AUD	NOK	PLN	NZD	BRL	AUD	NZD	PLN	BRL	SEK
P2	SEK	PLN	NZD	HUF	NOK	SEK	EUR	ZAR	PLN	HUF
P3	EUR	HUF	CHF	CZK	GBP	GBP	ZAR	HUF	BRL	NOK
P4	CAD	ZAR	GBP	JPY	CHF	CAD	CZK	CHF	HUF	NOK
P5	SGD	MXN	JPY	CAD	ZAR	SGD	MXN	JPY	AUD	NZD
Panel B: Monetary Policy Shocks Exposure Portfolios										
P1	AUD	BRL	NZD	PLN	NOK	AUD	NZD	BRL	SEK	PLN
P2	NOK	SEK	PLN	HUF	NZD	HUF	SEK	PLN	ZAR	NOK
P3	EUR	HUF	CAD	ZAR	CZK	EUR	CAD	NOK	ZAR	PLN
P4	GBP	CHF	CAD	CZK	ZAR	CHF	CZK	GBP	CAD	NOK
P5	SGD	JPY	MXN	CHF	GBP	SGD	JPY	MXN	CZK	CHF
Panel C: Information Shocks Exposure Portfolios										
P1	JPY	CHF	NOK	SGD	EUR	JPY	CHF	NOK	EUR	SGD
P2	NOK	SEK	EUR	CZK	ZAR	EUR	GBP	NOK	CZK	SGD
P3	HUF	GBP	CZK	PLN	ZAR	CAD	SEK	CZK	PLN	SGD
P4	AUD	CAD	HUF	NZD	MXN	AUD	MXN	NZD	BRL	CAD
P5	BRL	MXN	NZD	SGD	AUD	ZAR	HUF	NZD	MXN	BRL
Panel D: Carry Trade Portfolios										
P1	JPY	CHF	SGD	EUR	CZK	CHF	JPY	EUR	SEK	SGD
P2	EUR	SEK	CAD	CZK	NOK	GBP	CZK	JPY	EUR	SEK
P3	GBP	AUD	CAD	SEK	PLN	NOK	CAD	NZD	SGD	SEK
P4	NZD	HUF	ZAR	AUD	MXN	AUD	PLN	MXN	NZD	CAD
P5	BRL	MXN	ZAR	HUF	PLN	ZAR	BRL	MXN	HUF	NZD

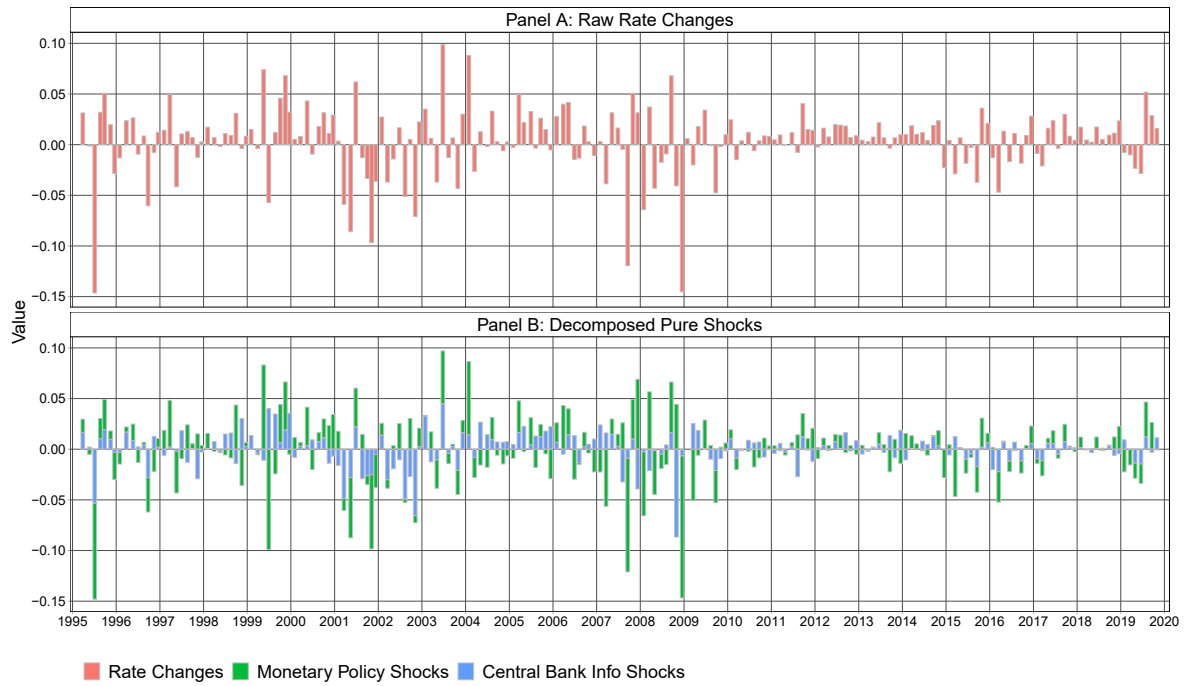
This table reports the currency composition of the five portfolios sorted based on rate changes exposure (Panel A), MP shocks exposure (Panel B), Info shocks exposure portfolios (Panel C), and the cross-section of the carry trade (Panel D) portfolios. We report the top five currencies entering each portfolio. The portfolios are re-balanced monthly. The sample period is between 03/1995-12/2008 for in-sample and 03/1995-07/2019 for out-of-sample.

Table B.8 Average rank weights.

07/1996-12/2008					01/2009-07/2019				
	Rate	MP	Info	Carry		Rate	MP	Info	Carry
JPY	-0.17	-0.21	-0.22	-0.25	CHF	-0.08	-0.14	-0.20	-0.23
CHF	-0.01	-0.12	-0.21	-0.20	JPY	-0.22	-0.23	-0.23	-0.18
SGD	-0.24	-0.24	0.03	-0.15	EUR	0.09	-0.01	-0.13	-0.14
EUR	0.04	-0.02	-0.11	-0.11	SEK	0.13	0.12	-0.02	-0.12
SEK	0.11	0.08	-0.07	-0.08	SGD	-0.22	-0.20	-0.08	-0.09
CAD	-0.13	-0.06	0.11	-0.07	GBP	-0.01	-0.05	-0.07	-0.09
CZK	-0.01	-0.03	-0.03	-0.04	CZK	-0.08	-0.11	-0.06	-0.06
NOK	0.18	0.10	-0.14	-0.01	CAD	-0.11	-0.03	0.05	-0.02
GBP	-0.07	-0.11	-0.08	0.02	NOK	0.01	0.01	-0.16	0.01
AUD	0.24	0.24	0.12	0.03	PLN	0.13	0.09	0.04	0.08
NZD	0.13	0.17	0.13	0.09	HUF	-0.01	0.05	0.15	0.08
PLN	0.16	0.17	0.09	0.11	NZD	0.19	0.19	0.15	0.09
HUF	0.04	0.06	0.04	0.15	AUD	0.23	0.23	0.13	0.10
ZAR	-0.08	-0.05	0.00	0.17	MXN	-0.17	-0.15	0.16	0.16
MXN	-0.21	-0.12	0.17	0.18	ZAR	0.04	0.09	0.17	0.19
BRL	0.06	0.18	0.22	0.23	BRL	0.07	0.13	0.09	0.22

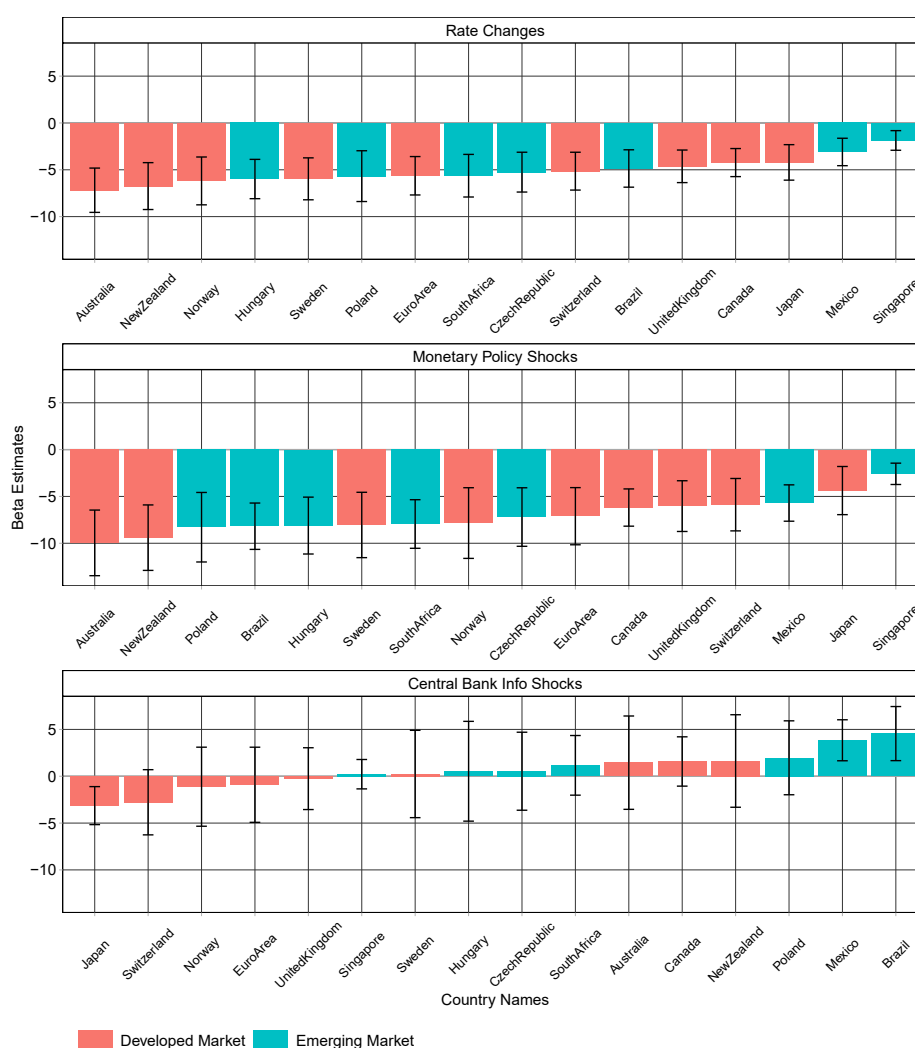
This table reports the average rank portfolio weights for the exposure portfolios and the carry trade portfolios.

Fig. B.1 Surprises and shocks measured over time.



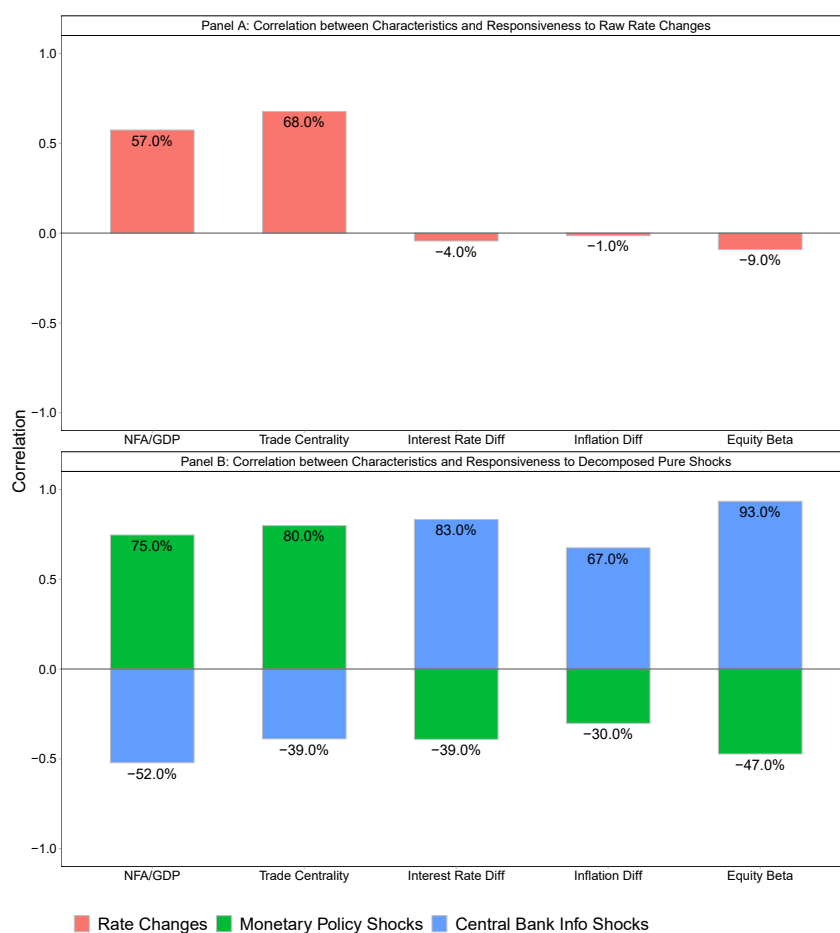
This figure reports the monetary policy-related variables measured over time. By analysing the co-movement of interest rates and stock prices in a narrow policy announcement window, we decompose interest rate innovations (denoted as Rate Changes) around the Federal Open Market Committee (FOMC) announcements into monetary policy and central bank information shocks.

Fig. B.2 Country-specific responsiveness to shocks.



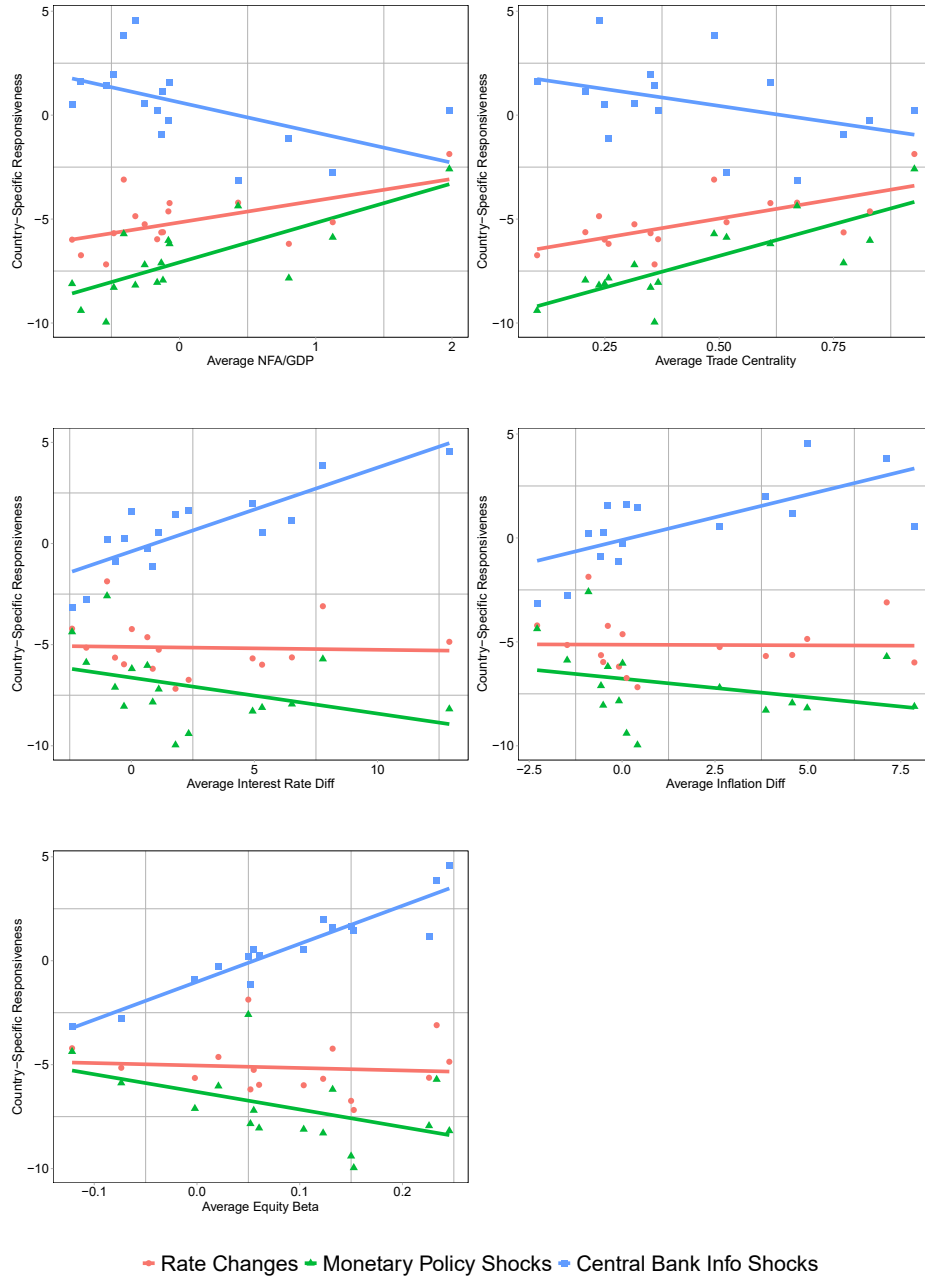
This figure plots the country-specific responsiveness to monetary policy-related variables. The country's average response to different monetary policy-related news/shock measures is estimated from the individual univariate regression. We report the estimated beta and their 90 per cent confidence interval based on Newey-West standard errors with optimal lags. The sample period is between 1996/01-07/2019.

Fig. B.3 Cross-sectional correlation between average characteristics and responsiveness to shocks.



This figure reports the cross-sectional correlation between the time-series average of currency characteristics and the effect of monetary policy-related variables on individual countries. The country's average response to different monetary policy-related news/shock measures is estimated from the individual univariate regression. The sample period is between 1996/01-07/2019.

Fig. B.4 Country-specific responsiveness to shocks and characteristics.



This figure plots the country-specific responsiveness to monetary policy-related variables against the time-series average of different currency characteristics. The country's average response to different monetary policy-related news/shock measures is estimated from the individual univariate regression. The sample period is between 1996/01-07/2019.

Fig. B.5 Country-specific responsiveness to shocks and characteristics (pre-2009).



This figure plots the country-specific responsiveness to monetary policy-related variables against the time-series average of currency interest rate differentials. The country's average response to monetary policy is estimated from the individual univariate regression $r_{i,t} = \theta_i \text{Shocks}_t + \varepsilon_{it}$, where i is the currency identifier, t is the date of the scheduled FOMC meeting, and r_{it} is the intraday currency spot return in the 30-minute window surrounding the FOMC press releases. Shocks_t is one of the structural shocks or innovations of interest: (1) policy rate changes, (2) purged policy shocks, and (3) central bank information shocks, respectively. A positive surprise/shock is tightening. The coefficient θ_i captures the policy exposure for each currency and is reported on the y-axis against their average interest rate differentials. The sample period is between 1996/01-12/2008.

Appendix C

C.1 Details on subsamples

In this section, we provide further details on subsamples. Firstly, it is noteworthy that, in each iteration, we only include currencies when there is no missing data for the capital account openness index and exchange rate regime (even for the full sample in this section). For example, due to the Taiwan dollar's missing data for the capital account openness index and exchange rate regime over the full sample period, we exclude TWD from any further analysis so that the 'new' full sample in this section contains 28 currencies rather than 29 previously.

Secondly, subsample *close (open)* is when we only include currencies of countries which have a score smaller (greater) than zero in the capital account openness index of Chinn and Ito (2006). Subsample *float* is when we restrict our universe of currencies to have exchange rate regime 3 or 4 in the classification of Ilzetzi et al. (2019) while subsample *fixed* is when we restrict the universe of currencies to have exchange rate regime 1 or 2. We also report results for combinations of the above four subsamples. For example, subsample *closefixed* is when we restrict the universe of currencies to meet both criteria: have a score smaller than zero in the capital account openness index and have an exchange rate regime of 1 or 2. A full list of subsamples is reported in Table 3.6.

Several observations can be made from subsampling results. Firstly, Table 3.6 provides the number of observations an individual currency enters the asset universe of the full sample, subsample *close*, *fixed* and *float*. It can be seen that there are more countries with open capital accounts than closed and there are more countries with floating exchange rate regimes than fixed. Turning to the top panel in Table 3.6, we report, for each sample, the maximum and the minimum number of available currency to invest over time and NAN% the percentage of time when there is no available currency to invest. One can see that the majority of floaters have a relatively open capital account (the *openfloats* ranges from 8 to 17 out of the 8 to 23 floaters).

C.2 Additional tables and figures

This section contains additional tables and figures.

Table C.1 Classification of exchange rate regime.

The coarse classification codes are:	
R1	• No separate legal tender
R1	• Pre announced peg or currency board arrangement
R1	• Pre announced horizontal band that is narrower than or equal to $\pm 2\%$
R1	• De facto peg
R2	• Pre announced crawling peg
R2	• Pre announced crawling band that is narrower than or equal to $\pm 2\%$
R2	• De facto crawling peg
R2	• De facto crawling band that is narrower than or equal to $\pm 2\%$
R3	• Pre announced crawling band that is wider than or equal to $\pm 2\%$
R3	• De facto crawling band that is narrower than or equal to $\pm 5\%$
R3	• Moving band that is narrower than or equal to $\pm 2\%$ (i.e., allows for both appreciation and depreciation over time)
R3	• Managed floating
R4	• Freely floating
R5	• Freely falling
R6	• Dual market in which parallel market data is missing

This table shows the Ilzetzi et al. (2019) classification of the exchange rate regime.

C.2 Additional tables and figures

Table C.2 Descriptive statistics of excess returns to individual currencies.

Currency		Sample		Excess Return		Forward Discount				No. of Observations			
Country/Area	Abbrev.	Start	End	Mean	SD	Mean	SD	Max	Min	All	Close	Fixed	Float
United Kingdom	GBP	199403	201812	0.08	0.88	0.68	0.01	0.07	-0.04	297	0	0	297
Switzerland	CHF	199403	201812	-0.14	1.08	-1.58	0.02	0.17	-0.07	297	0	42	232
Japan	JPY	199403	201812	-3.07	1.06	-2.84	0.02	0.13	-0.22	297	0	0	297
Canada	CAD	199403	201812	0.08	0.81	0.04	0.01	0.04	-0.03	297	0	99	198
Australia	AUD	199403	201812	1.55	1.18	1.56	0.02	0.07	-0.19	297	0	0	297
New Zealand	NZD	199403	201812	3.26	1.22	2.59	0.02	0.23	-0.12	297	0	0	297
Sweden	SEK	199403	201812	-0.21	1.12	0.26	0.02	0.18	-0.09	297	0	115	182
Norway	NOK	199403	201812	0.01	1.13	0.69	0.03	0.15	-0.35	297	0	0	297
Denmark	DKK	199403	201812	-0.15	0.95	-0.19	0.02	0.14	-0.07	297	0	297	0
Euro Area	EUR	199901	201812	-0.40	0.96	-0.25	0.01	0.04	-0.09	238	0	0	238
Germany	DEM	199403	199901	-1.57	0.94	-1.62	0.01	0.03	-0.04	58	0	0	58
Hong Kong	HKD	199403	201812	-0.15	0.05	-0.10	0.01	0.09	-0.01	297	0	297	0
South Africa	ZAR	199403	201812	-2.11	1.50	6.72	0.04	0.43	-0.18	256	256	0	244
Singapore	SGD	199403	201812	-0.44	0.57	-0.99	0.06	0.19	-2.85	297	0	0	297
Czech Republic	CZK	199701	201812	1.43	1.18	0.59	0.02	0.16	-0.05	263	37	31	232
Hungary	HUF	199710	201812	3.12	1.33	4.74	0.03	0.07	-0.02	253	37	130	123
India	INR	199710	201812	1.72	0.59	4.71	0.02	0.08	-0.02	253	253	208	45
Indonesia	IDR	199701	201812	1.35	1.55	8.04	0.06	0.38	-0.61	178	94	87	78
Malaysia	MYR	199701	201812	-1.74	0.93	1.51	0.01	0.19	-0.06	178	147	7	171
Mexico	MXN	199701	201812	2.91	1.07	6.93	0.04	0.19	0.00	263	22	0	263
Philippines	PHP	199701	201812	0.78	0.81	3.83	0.02	0.18	-0.01	263	263	67	190
Poland	PLN	200202	201812	2.90	1.35	2.28	0.01	0.04	-0.02	201	153	0	173
Saudi Arabia	SAR	199701	201812	0.14	0.04	0.14	0.00	0.02	-0.02	263	0	263	0
South Korea	KRW	200202	201812	1.87	1.06	0.89	0.01	0.02	-0.07	201	71	0	201
Taiwan	TWD	199701	201812	-1.39	0.43	-0.91	0.02	0.09	-0.07	263	0	0	0
Thailand	THB	199701	201812	0.96	0.87	2.01	0.03	0.31	-0.01	263	263	7	250
Brazil	BRL	200403	201812	7.05	1.53	8.87	0.02	0.08	-0.01	176	106	0	176
Russia	RUB	200403	201812	1.37	1.36	5.92	0.04	0.30	-0.02	174	56	53	106
Israel	ILS	200403	201812	1.47	0.77	0.21	0.01	0.01	-0.01	176	0	0	176

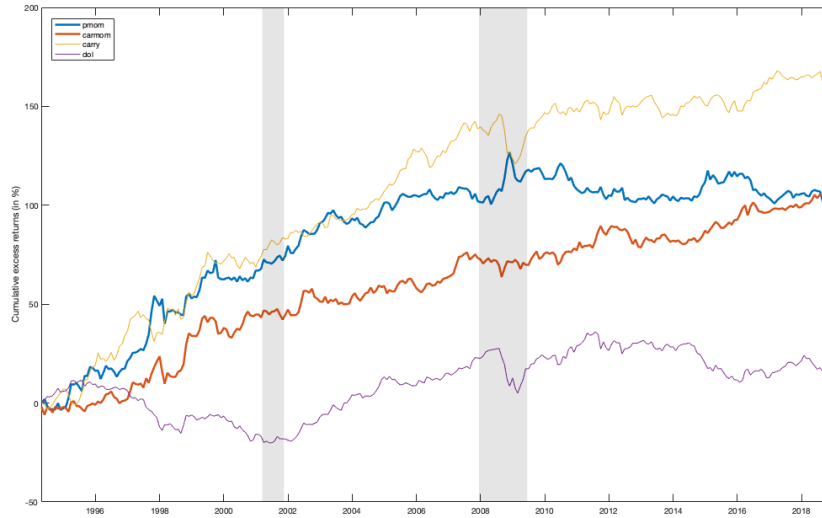
This table shows descriptive statistics for individual currencies. Means and standard deviations for daily log excess returns and forward discounts are annualised and in per cent. Maximum and minimum forward discounts are daily and in percentage. This table also reports the number of observations a currency enters the full sample as well as the subsamples of countries with the close capital account ($kaopen < 0$) and fixed (regime 1 & 2) and float (regime 3 & 4) exchange rate regime. Taiwan has zero observation in all subsamples due to the missing data for its *kaopen* index and exchange rate regime. The sample period runs from March 1994 to December 2018.

Table C.3 Descriptive statistics of the three-day abnormal returns around trade announcement.

	Panel A: 3-day Cum. Return				Panel B: Absolute Value of 3-day Cum. Return			
	Mean%	tstat	$(f - s)\%$	$\Delta s\%$	Mean%	tstat	$ f - s \%$	$ \Delta s \%$
GBP	-0.0376	-0.76	-0.0115	-0.0261	0.5538	13.93	0.0149	0.5535
CHF	-0.0603	-1.24	-0.0390	-0.0213	0.6576	14.59	0.0416	0.6493
JPY	-0.0032	-0.05	-0.0528	0.0497	0.8433	15.06	0.0530	0.8407
CAD	-0.0877	-1.79	-0.0191	-0.0686	0.5509	16.49	0.0205	0.5469
AUD	0.0043	0.08	-0.0015	0.0057	0.6934	15.87	0.0213	0.6916
NZD	0.0653	0.99	0.0077	0.0576	0.7936	14.27	0.0206	0.7915
SEK	-0.0467	-1.00	-0.0180	-0.0287	0.6242	14.48	0.0248	0.6227
NOK	0.0111	0.27	-0.0090	0.0202	0.5821	16.75	0.0178	0.5811
DKK	-0.0224	-0.59	-0.0220	-0.0004	0.5027	17.11	0.0253	0.4985
EUR	-0.0244	-0.61	-0.0223	-0.0021	0.4863	14.27	0.0229	0.4853
DEM	-0.0519	-0.49	-0.0397	-0.0122	0.5989	12.46	0.0405	0.5935
HKD	-0.0416	-1.18	-0.0209	-0.0207	0.4686	16.15	0.0225	0.4673
ZAR	-0.1939	-2.28	0.0607	-0.2546	0.9552	12.38	0.0612	0.9624
SGD	-0.0114	-0.38	-0.0305	0.0190	0.3431	11.46	0.0318	0.3394
CZK	0.0158	0.29	-0.0147	0.0305	0.6907	15.15	0.0283	0.6926
HUF	0.0433	0.72	0.0356	0.0077	0.7305	15.16	0.0450	0.7287
INR	-0.0231	-0.54	0.0337	-0.0568	0.4993	16.85	0.0384	0.4989
IDR	0.2437	1.42	0.0751	0.1686	1.0029	5.09	0.0751	0.9950
MYR	-0.0536	-0.94	-0.0007	-0.0529	0.5281	5.89	0.0125	0.5265
MXN	0.1180	1.60	0.0600	0.0581	0.8035	12.46	0.0600	0.7881
PHP	0.0829	1.42	0.0240	0.0589	0.5990	9.54	0.0306	0.5981
PLN	0.0464	0.66	0.0084	0.0381	0.7972	8.72	0.0156	0.7964
SAR	-0.0240	-0.62	-0.0203	-0.0037	0.4862	14.92	0.0211	0.4856
KRW	0.0200	0.27	-0.0082	0.0282	0.5988	6.20	0.0120	0.5985
TWD	-0.0730	-2.24	-0.0327	-0.0402	0.4514	17.15	0.0366	0.4487
THB	0.0239	0.43	0.0001	0.0237	0.5449	11.32	0.0213	0.5437
BRL	0.1335	1.47	0.0888	0.0447	0.9556	10.21	0.0888	0.9488
RUB	0.1056	1.48	0.0514	0.0542	0.6991	6.87	0.0569	0.7003
ILS	0.0265	0.51	-0.0155	0.0419	0.5116	10.96	0.0167	0.5129

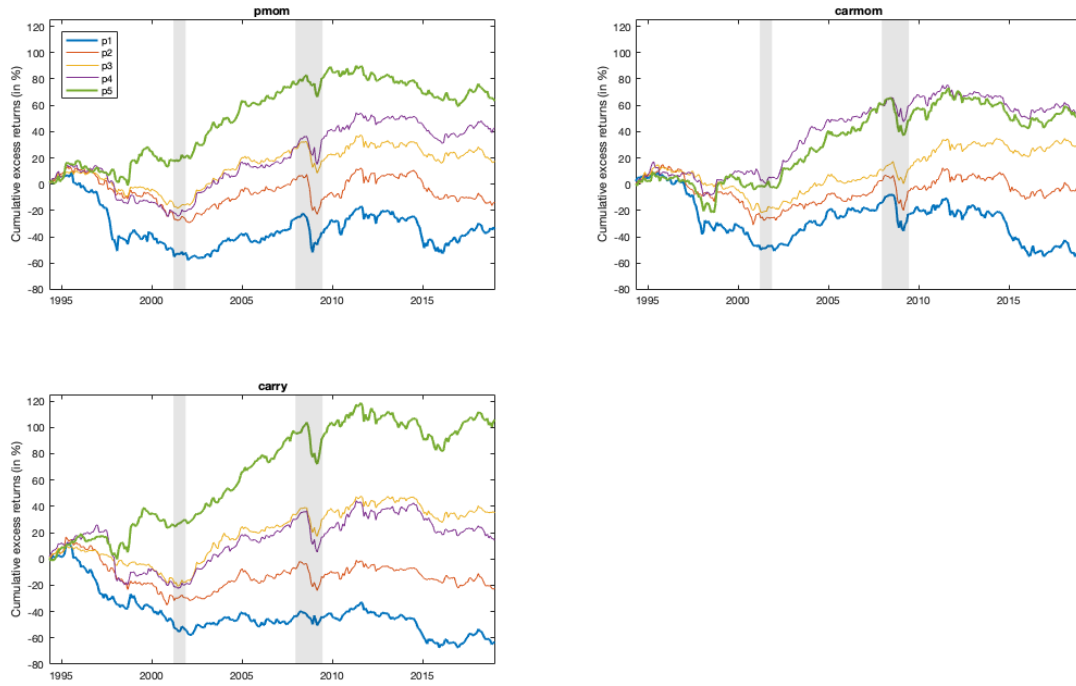
This table shows descriptive statistics for the three-day abnormal returns ($CAR3$) for individual currency in Panel A and the absolute value of $CAR3$ for individual currency in Panel B. We report the average value of $CAR3$ or $|CAR3|$, HAC t-statistics of the null hypothesis that the mean $CAR3$ or $|CAR3|$ is different from zero. $(f - s)$ or $|(f - s)|$ represent the return earned from the (absolute value of) forward discount while Δs or $|\Delta s|$ represent the return earned from the (absolute value of) spot rate changes. The sample period runs from March 1994 to December 2018.

Fig. C.1 Cumulative returns to currency strategies.



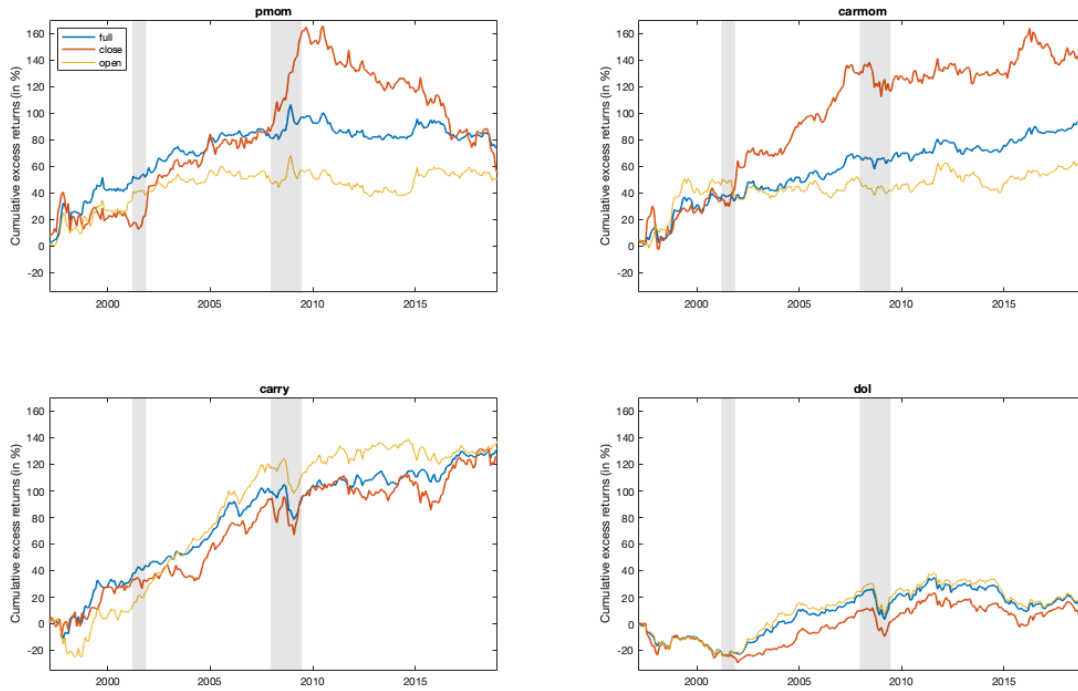
This figure shows cumulative log excess returns (not adjusted for transaction costs) accruing to the four currency strategies. The four strategies are past price momentum *PMOM*, trade news momentum *CARMOM*, carry trade *CARRY* and dollar risk factor *DOL*. The bold blue line shows returns to past price momentum strategy with a 1-month formation period, the bold red line shows returns to trade news momentum rebalanced at every news release, the thing yellow line shows returns to carry trade strategy rebalance at the end of every month, whereas the thing purple line shows returns to the dollar risk factor. Shaded areas correspond to NBER recessions.

Fig. C.2 Cumulative returns to the cross-section of sorted currency portfolios.



This figure shows cumulative log excess returns accruing to the five portfolios of past price momentum *PMOM*, trade news momentum *CARMOM* and carry trade *CARRY*. The bold blue line shows returns to portfolio one *p1* for each strategy, the thin red line shows returns to portfolio two *p2*, and so on, and the bold green line shows returns to portfolio five *p5*. The *p1* to *p5* corresponds to currencies with increasingly higher past 1-month cumulative returns in figure *pmom*, higher 3-day cumulative return around trade news announcement dates in figure *carmom* and higher forward discount in figure *carry*. Shaded areas correspond to NBER recessions.

Fig. C.3 Cumulative returns and capital account openness.



This figure shows cumulative log excess returns accruing to different currency strategies, including price momentum (*PMOM*), trade news momentum (*CARMOM*), carry trade (*CARRY*) and dollar risk factor (*DOL*). In each subplot, the same strategy is constructed using a full sample of all available currencies (blue line) and subsamples of currencies of countries with open capital accounts (yellow line) and subsamples of currencies of countries with relatively closed capital accounts (red line). Shaded areas correspond to NBER recessions.

Fig. C.4 Cumulative returns and exchange rate regimes.



This figure shows cumulative log excess returns accruing to different currency strategies, including price momentum (*PMOM*), trade news momentum (*CARMOM*), carry trade (*CARRY*) and dollar risk factor (*DOL*). In each subplot, the same strategy is constructed using a full sample of all available currencies (blue line) and subsamples of currencies with the fixed exchange rate regime 1 or 2 (yellow line) and subsamples of currencies with the float exchange rate regime 3 or 4 (red line). Shaded areas correspond to NBER recessions.

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