Technology Diffusion and Currency Risk Premia

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Abstract

We identify a unique dimension of currency carry trade related to cross-country technology transmission. Technology diffusion is measured by the R&D ingredient embodied in manufactured goods imports. Empirical evidence shows that the difference in tech diffusion explains the cross-section of currency excess returns. Countries adopting more technologies tend to have higher interest rates and excess returns. Using a two-country model with technology transmission, we show that the adoption sector insulates tech-diffusion countries from global productivity shocks, resulting in lower risk exposure. Consequently, investors require a risk premium for holding high-interest-rate currencies as compensation for their procyclical returns.

Keywords: Exchange Rate; Carry Trade Portfolio; UIP Condition; Cross-Country Technology Spillover; Technology Adoption.

JEL Classification: F31; G12; G15; O33

1 Introduction

This paper examines the role of technology diffusion in carry trade strategies in a cross-country environment. First, we provide empirical evidence that cross-country technology diffusion generates heterogeneous risk exposure and is a fundamental determinant of currency risk premia. Then we rationalize this finding in a simple two-country environment by showing that the endogenous resource reallocation between innovation and adoption sectors accounts for the observations. Carry trade is a currency investment strategy that exploits deviations from the uncovered interest rate parity (UIP) condition. The UIP indicates that the difference in the yields of foreign and domestic risk-free securities (e.g., government bonds) must be offset by an analogous depreciation of the high-interest-rate currency in expectation. However, many studies have documented the empirical rejection of the UIP (e.g., Bilson, 1981; Fama, 1984; Hansen and Hodrick, 1980), primarily associated with a time-varying risk premium charged by investors in the foreign exchange (FX) market. Other studies (e.g., Hassan and Mano, 2019; Lustig, Roussanov, and Verdelhan, 2011a; Lustig and Verdelhan, 2007) show that a naive strategy that involves a long position in high-interest-rate currencies and a short position in low-interest-rate currencies (i.e., the carry strategy) generates prominent excess returns.

Using the UN Comtrade database at the six-digit level, we find that the prevalent cross-country currency risk premia can be attributed to different abilities in adopting research and development (R&D) in the intensive margin of trade. Technology diffusion, a dynamic consequence of adoption, is a key dimension of the carry trade strategy. In this paper, we provide empirical and theoretical answers to the following questions: How does the difference in the ability of technology adoption lead to heterogeneous consumption risk exposure over the business cycle? How does this heterogeneity in the risk exposure contribute to a persistent currency risk premium in the long run?

We develop a measure of technology diffusion using knowledge concentration in the global trade environment. The factor captures the ingredient of R&D incorporated in the quantity of manufacturing goods imports. Specifically, we first construct the R&D-adjusted intensive margin of import for each country pair and then derive the tech-diffusion index of a specific importer by constructing a concentration measure over its trade partners. Intuitively, a high tech-diffusion measure implies that a country is central to the global R&D flow, while a low tech-diffusion measure indicates that the country is peripheral to the global R&D flow. Our hypothesis is that high-interest-rate countries exhibit a higher concentration of technology diffusion because they receive more R&D goods from their trade partners. On the other hand, low-interest-rate countries take on R&D themselves and export a large quantity of high-technology goods to the high-interest rate countries.[1]

Table 1 provides an overview of the R&D spending in major large economies of the world, together with their average forward discount and currency excess returns against the U.S. dollar.[2] Overall, we find that currencies with a high R&D ratio demonstrate low forward discounts. In particular, Japan and Switzerland, considered typical funding currencies in the FX market, actively conduct R&D on their own. In contrast, New Zealand and Australia, well known for their high forward discounts and considered investment currencies, are reluctant to innovate. Moreover, the pattern of currency excess return is generally aligned with the forward discount, indicating the profitability of the carry trade strategy and the violation of the UIP. This finding invites us to consider the fundamental link between international knowledge diffusion and the carry trade return.

We start with a cross-sectional regression of future currency excess returns on our tech-diffusion measure while controlling for country size, inflation, and trade openness. In line with our conjecture, we find that tech diffusion is a strong and positive predictor for the cross-section of currency return and interest rate difference. The predicting power still exists after we control for countries' GDP shares à la Hassan (2013), which is considered to be the key explanatory factor for the carry trade return in developed economies. To further assess the role of tech diffusion in explaining cross-sectional currency excess returns, we construct a common risk factor. Specifically, we consider a zero-cost investment strategy that goes long in currencies of high-tech-diffusion countries (i.e., adopters) and short in the low-tech-diffusion economies (i.e., innovators). Over the sample period

[1] A related paper is Gavazzoni and Santacreu (2020), who use a quantitative model to show that international technology transmission through adoption can account for the cross-country propagation of risk and asset price puzzles. They also provide empirical evidence to show that the country-pair R&D content of trade is positively correlated with stock market return comovement and negatively correlated with bilateral exchange rate volatility. Our paper, instead, focuses on the transmission of technology from innovation to adoption countries in an asymmetric environment and considers the asset-pricing implications.

[2] The group is called "G10 currencies," and it comprises what are considered the most traded and liquid currencies in the FX market.

Table 1: Currency Returns and Global R&D

Country	Forward Discount	Excess Return	R&D Ratio (%)
Japan	-2.64	-2.12	2.43
Switzerland	-1.87	-0.26	2.14
Euro	-0.74	-0.84	1.94
Germany*	-0.60	-1.11	2.49
Sweden	-0.05	-0.95	2.66
Canada	0.04	-0.03	1.52
United Kingdom	0.58	0.17	1.52
Norway	0.77	-0.14	1.00
Australia	1.77	1.91	1.37
New Zealand	2.38	3.39	1.01
United States	-	-	2.62

Notes: This table presents average forward discounts and excess returns from January 1993 to December 2019 for the "G10" currencies from the perspective of a U.S. dollar investor. * For Germany, the numbers are based on the return of the Deutsche mark prior to 1999 and the return of the euro afterward.

from 1993 to 2019, the strategy offers an annualized return of 2.82% for the OECD (Organization and Economic Co-operation and Development) countries and 3.50% for the G10 currencies with Sharpe ratios of 42% and 43%, respectively. Over the same period, a monthly rebalanced carry trade strategy exhibits similar dynamics, achieving an average return of 5.00% before transaction costs for OECD countries and 4.70% for the G10 currencies.

Next, we test the significance of the tech diffusion using a two-factor asset-pricing model that comprises a level factor and a slope factor as in Lustig, Roussanov, and Verdelhan (2011a). The results show that the tech-diffusion factor is priced in the cross-section of currency excess returns and that it can capture most of the carry trade variability. Also, the portfolios sorted on tech-diffusion betas lead to the same monotone pattern of excess returns and interest rates. To do that, we compute each currency's beta to the tech-diffusion factor by running a 36-month rolling-window regression that ends in period $t-1$. Buying a high-beta portfolio yields higher currency excess returns than buying a low-beta portfolio, with a high-minus-low spread of 4.40% (3.27%) per annum in the OECD countries (G10 currencies). The result implies that the sorts based on the tech-diffusion measure indeed unveil a common risk factor that is fundamental to the carry trade portfolios.

Two studies closely related to our paper are Ready, Roussanov, and Ward (2017) and Richmond (2019), who also demonstrate the success of trade-based factors in explaining the cross-section of the currency risk premium. Specifically, Ready, Roussanov, and Ward (2017) show that countries' relative advantages in producing either basic goods or final goods account for their different risk exposure, resulting in a spread of currency excess returns. They construct an empirical measure of the import ratio to capture the extent to which a country specializes in the production of basic commodities. Meanwhile, Richmond (2019) builds an empirical centrality measure that echoes the one in a trade network model and shows that countries that are more central in the global trade network have lower interest rates because they are more correlated with global consumption growth. Although our tech-diffusion measure is also based on the disaggregate level of trade data and is used to predict the cross-sectional currency returns, it conveys different information.[3] The measure reflects the R&D ingredients of trade flows in the intensive margin of import. Loosely speaking, the high-interest-rate countries adopt technologies by importing R&D goods, while the low-interest-rate countries design them.

We show that countries' relative rankings based on our tech-diffusion measure and the above alternative measures do not perfectly correlate. For example, Korea and Switzerland are high-tech-diffusion countries, but they produce final complex goods and import basic goods. On the contrary, Portugal and Finland have a low-tech-diffusion index but are periphery to the global trade network. Comparatively, the connection between the tech-diffusion measure and centrality is even looser than the connection between tech diffusion and the import ratio. In addition, we also test the predicting power of orthogonalized risk factors. We first extract the estimated residuals from a contemporaneous regression of the tech-diffusion factor on the import-ratio (or centrality) factor. Then we include the orthogonalized risk factors in the asset-pricing model to consider their predictabilities. The orthogonalized part of the tech-diffusion factor still has a strong predicting

[3]The data used to construct the tech-diffusion factor is very different from the data used to construct the import ratio in Ready, Roussanov, and Ward (2017). For example, we focus on the trade of manufacturing goods to consider the R&D ingredients in the trade flows, and we exclude the data on raw materials and natural resources because these products barely reflect any technology content.

power for the cross-section of currency excess returns, and the two-factor models can explain 37% and 75% of the cross-sectional variation in the carry trade returns.

Our main conclusion that tech diffusion is a key determinant of cross-sectional currency carry return is robust to alternative specifications. First, we use the carry trade portfolios sorted on the half-sample forward discount as test assets and find that our tech-diffusion factor has a stronger predicting power in explaining the unconditional currency risk premium. This is not surprising given that the tech-diffusion index captures countries' heterogeneous risk exposure, which is an unconditional property in its nature. Also, to guard against the possibility of a "lucky" factor à la Harvey and Liu (2021) and Lewellen, Nagel, and Shanken (2010), we show that our empirical results apply to a larger group of testing assets that include both the carry trade and tech-diffusion portfolios.

We build a simple two-country environment to understand how technology adoption accounts for the heterogeneous exposure and currency excess returns. The process of innovation and adoption follows Comin and Gertler (2006) and Comin, Loayza, Pasha, and Serven (2014). The economy lasts for two periods. In the first period, a social planner decides the resource allocation between innovating and adopting, while in the second period, patents are used for production, and the trade of intermediate goods happens. We assume that the home country can only innovate while the foreign country chooses the optimal investment between the innovation and adoption sectors. A domestically invented patent only requires the domestic intermediate goods as production inputs, while the adopted patent requires the intermediate goods imported from abroad. As a result, the relative profitability of adoption depends on the fluctuation of the real exchange rate, which in turn determines the investment decision in the first place.

The model indicates that endogenous adoption creates heterogeneous risk exposure between the two countries. Under a positive shock, the home country expands the innovation effort due to the higher profitability. The increased production in the home country also benefits the foreign economy due to the depreciated real exchange rate (cheaper intermediate exports) and diffusion externality. As a result, the foreign country expands its adoption sector more than the innovation sector. The opposite is true under a negative shock: the decline in the home country's outputs makes the intermediate imports more expensive in the foreign economy, and since the foreign country quickly shifts back to its innovation sector, its consumption declines by less than that of the home country.[4]

The presence of the adoption sector in the foreign country indicates its greater ability to shift risk toward the home country under global productivity risk. Importantly, we show that the endogenous rebalancing between innovating and adopting sectors creates an internal link between the two countries and produces exchange rate dynamics supported by the data. Specifically, home consumption is more closely correlated with global output than foreign consumption. The stronger (weaker) precautionary saving motive in the home (foreign) country implies a negative (positive) interest rate spread and currency excess return. As a result, the carry trade strategy, going long in the foreign currency and short in the home currency, leads to a spread of interest rates and currency returns. Because the foreign currency depreciates in the downturn, the carry trade return is procyclical and so is the home country's net export.

In sum, this paper shows that technology diffusion is a fundamental pricing factor in the cross-section of currency returns. On the currency side, high-interest-rate currencies load positively on the tech-diffusion factor, and low-interest-rate currencies load negatively. As a result, carry traders require a risk premium for holding the high-tech-diffusion currencies as compensation for the elevated exchange rate risk. On the business-cycle side, the endogenous adoption allows high-interest-rate economies to hedge against global productivity shocks, while the more R&D innovation risks are shifted to the low-interest-rate countries.

Connection to the Literature. Recent advances in the literature suggest that carry trade profitability can be attributed to a risk premium acquired by FX investors that seek to compensate themselves for adverse movements of the exchange rate under bad states of the world (e.g., Lustig, Roussanov, and Verdelhan, 2011a; Lustig and Verdelhan, 2007). In particular, Lustig, Roussanov, and Verdelhan (2011a) show that two tradable risk factors that are highly correlated with the first two principal components of currency portfolios, sorted on interest rate differentials, are enough to price the cross-section of currency returns. The first risk factor resembles a strategy that invests in

[4]The adoption sector serves as a hedging device in the foreign country. In good times, the adoption sector allows the foreign country to take a ride on the higher growth opportunity in the home country, while in bad times, the foreign country can partly insure against the negative shock by reallocating resources toward its own innovation.

a basket of all marketable currencies each time and liquidates its position by borrowing the dollar. This strategy is mainly driven by the U.S. business cycle, and thus it is labeled as a dollar factor (DOL, as in Lustig, Roussanov, and Verdelhan, 2011b,0). This factor is highly correlated with the first principal component of the carry trade portfolios, representing a level factor. The second risk factor is a carry trade portfolio that invests in a basket of high-interest-rate currencies and borrows from the basket of low-interest-rate currencies. This factor lies behind the second principal component and is labeled as the carry factor (HML^{FX}).

Many papers explore the fundamental determinants of the carry trade strategy. They use either the structural asset-pricing approach or build structural models to investigate the economic mechanism behind currency risk premia. These papers include but are not limited to Colacito, Riddiough, and Sarno (2020), Dahlquist and Hasseltoft (2020), Della Corte, Riddiough, and Sarno (2016), Filippou and Taylor (2017), Hassan (2013), Jiang (2022), Menkhoff, Sarno, Schmeling, and Schrimpf (2012), Ready, Roussanov, and Ward (2017), and Richmond (2019). In particular, Richmond (2019) uses a trade network model to argue that the low-interest-rate countries are usually more central to trade networks because their consumption growth is more exposed to global consumption growth shocks. Ready, Roussanov, and Ward (2017) show that the relative advantage in producing basic or final goods can account for heterogeneous productivity risk exposure across countries. The commodity currency appreciates in good times and depreciates in bad times, leading to a risk premium charged by international investors and a persistent carry trade return. Similar to these two papers, the construction of our measure is also based on the bilateral trade data, but we emphasize the effect of R&D diffusion on the cross-country productivity comovement and currency excess returns.

In addition to the trade-based factors, Hassan (2013) claims that countries' economic sizes (GDP shares) are a fundamental factor that can explain a large fraction of cross-sectional currency return variations. Naturally, larger economies are more able to insure against consumption shocks, resulting in a low currency return. More recently, Jiang (2022) extends the fiscal theory of price level (FTPL) to an open-economy environment and shows that the real exchange rate responds to fiscal shocks through a government's intertemporal budget constraint. Using a sample of developed countries, he finds that countries' fiscal exposure to a common factor is aligned with their currencies' exposure to the carry trade return. Della Corte, Riddiough, and Sarno (2016) show that countries' net foreign asset positions (nfa) together with the structure of liabilities (ldc) can explain the cross-sectional variation in currency excess returns. Investors are compensated for holding net debtor countries' assets whose currencies depreciate in bad times. Menkhoff, Sarno, Schmeling, and Schrimpf (2012) argue that a global volatility factor along with a dollar factor demonstrates strong pricing ability for interest-rate-sorted portfolios. They show that investment currencies load negatively on the global volatility innovations, while the opposite holds for the funding currencies, meaning that the latter provides a hedge against FX volatility risk. Lastly, Colacito, Riddiough, and Sarno (2020) establish a connection between currency excess returns and the relative strength of the business cycle in different countries. They show that the business cycle factor can predict currency returns in both the cross-sectional and the time-series dimensions.

Our paper also contributes to the strand of studies that uses the innovation model for asset-pricing implications (e.g., Comin, Gertler, and Santacreu, 2009; Croce, Nguyen, and Schmid, 2012; **?**; **?**; Kung and Schmid, 2015). In a closed-economy environment, Kung and Schmid (2015) embed R&D into a production economy with recursive preference and show that agents' uncertainty about the economy's growth prospect drives up the risk premium and generates the low-frequency fluctuation of macro variables. Croce, Nguyen, and Schmid (2012) demonstrate that under model uncertainty, fiscal policies aimed at short-run stabilization may increase the amount of long-run risk and depress economic growth and welfare. In an international environment, Comin, Gertler, and Santacreu (2009) develop a model to show that the shock to innovations and the process of costly technology adoption can change people's beliefs about countries' growth potentials and thus accounts for the variation in outputs and stock prices.

Roadmap. Section 2 describes our dataset and the construction of the tech-diffusion measure. Section 3 shows the main empirical results, which include the cross-sectional regression, summary statistics of portfolios, the asset-pricing test for a two-factor model, and unconditional currency returns. Section 4 provides an alternative measure that complements our tech-diffusion index and contrasts our currency risk factor with other trade-based factors in the literature. Section 5 builds a model to explain the economic mechanism behind our empirical findings. Section 6 concludes the paper.

2 Data and Currency Portfolios

The exchange rate data are collected from Barclays and Reuters via Datastream. To construct currency excess returns, we use the daily spot and one-month forward exchange rates against the U.S. dollar with the period spanning from January 1993 to December 2019.[5] We construct an end-of-month series for the daily spot and forward rates as in Burnside et al. (2011). In particular, the data are not averaged but represent the exchange rates on the last trading day of each month. While Lustig et al. (2011a) start their sample from an earlier date of 1983, very few countries have exchange rate data and trade data available in the beginning years. We also eliminate the country-episodes that feature strong violations of covered interest rate parity (CIP).[6] In the main analysis, we consider mid quotes, defined as the mean of the bid and ask quotes of each currency.

We denote S_t and F_t as the spot and one-month forward exchange rates, respectively, for a particular country, expressed in units of foreign currency per one U.S. dollar.[7] The log spot and forward exchange rates are given by $s_t = \log(S_t)$ and $f_t = \log(F_t)$. Assuming that covered interest parity holds, we have that the forward discounts are equal to the interest rate differentials; that is $f_t - s_t \approx \hat{i}_t - i_t$, where $\hat{i}_t$ and i_t are the nominal interest rates in the foreign country and the U.S. economy, respectively. The log excess return from t to t+1 (rx_{t+1}) is defined as the payoff of a strategy that buys a foreign currency in the forward market at time t and then sells it in the spot market after one month, which is expressed as

$$rx_{t+1} = f_t - s_{t+1}. \tag{1}$$

The formula can be approximated by $rx_{t+1} \approx \left(\hat{i}_t - i_t\right) - \Delta s_{t+1}$. It says that the currency excess return consists of two parts: the interest rate differential and the rate of appreciation in the foreign

[5] We use the three-month forward rate data when calculating the real interest rate.

[6] Figure C.8 in appendix C plots the number of countries with available data during our sample episode.

[7] The nominal appreciation of a foreign currency is reflected by a decline in S_t.

currency. Similarly, the arithmetic excess return is computed as

$$RX_{t+1} = \frac{F_t - S_{t+1}}{S_t} = \frac{F_t - S_t}{S_t} - \frac{S_{t+1} - S_t}{S_t}. \tag{2}$$

The bilateral trade data are obtained from the UN Comtrade. We adopt the six-digit level of disaggregation (based on the Standard International Trade Classification [SITC] code) to differentiate between manufactured goods, raw materials, and natural resources and identify the technology level in each product. Since our paper studies the effect of cross-country R&D spillover, we drop all products other than manufactured goods. [8] The R&D and GDP data are obtained from the World Bank's World Development Indicator (WDI). Quarterly consumption data come from OECD statistics. Because carry trade return is calculated at a monthly frequency, we interpolate the trade and macro data by keeping their previous-year values constant until a new value becomes available.[9]

We construct two samples for our analysis. The full sample consists of 27 OECD countries for which we have exchange rate and R&D data and where the bid-ask spreads of their currencies show enough liquidity. The full sample (referred to as "all countries") includes Australia, Austria, Belgium, Canada, Czechia, Denmark, the euro area, Finland, France, Germany, Greece, Hungary, Ireland, Israel, Italy, Japan, the Netherlands, New Zealand, Norway, Portugal, Slovakia, Slovenia, South Korea, Spain, Sweden, Switzerland, and the United Kingdom. The second group (referred to as "G10 currencies") is a subset of the full sample and comprises what are considered the most traded and liquid currencies in the FX market. These are ten currencies: Australia, Canada, the euro area, Germany (replaced by the euro since 1999), Japan, New Zealand, Norway, Sweden, Switzerland, and the United Kingdom. The tenth currency is the U.S. dollar itself, which serves as a base currency. The data of euro area countries are excluded after the introduction of the euro in January 1999. Some countries entered the eurozone after that date. In that case, their exchange rates are excluded from the sample at a later date. [10]

[8] In the empirical exercise of Gavazzoni and Santacreu (2020), they also use the bilateral trade flows for seven manufacturing industries to consider the effect of R&D spillover on cross-country asset price comovements.

[9] A similar approach has been used by other studies such as Della Corte et al. (2016) and Ready et al. (2017).

[10] We also take into account the transaction cost of carry trade strategies by constructing net excess returns. Figure B.3 in appendix B displays portfolio returns after considering the bid-ask spread.

Tech-Diffusion Measure. The focus of this paper is to study the effect of R&D spillover on the heterogeneous productivity risk exposure and consider its implication on currency excess returns. Generally, studies in the literature (e.g., Coe and Helpman, 1995; Grossman and Helpman, 1991) claim that if a country imports primarily from high-R&D partners, it is likely to receive more technologies embedded in intermediate goods, which benefit the productivity in its own production. [11] In other words, the technology transfers across countries contribute to the increase in productivity of a country importing such technologies. Many papers (e.g., Comin and Hobijn, 2010; Comin and Mestieri, 2010; Keller, 2004; Nishioka and Ripoll, 2012) use R&D data at both the aggregate and disaggregate levels to confirm that foreign innovation and the R&D content of trade contribute to cross-country productivity variations.

We follow the spirit of Gavazzoni and Santacreu (2020) and construct a measure of the R&D-weighted import to evaluate a country's absorption of technologies in the trade market.[12] First, we define the trade intensity $TI_{imp,exp}$ as the dollar value of all imported products from a country *exp* to a country *imp*. To control for the country size, the trade intensity is divided by GDPs in both the exporting and importing economies, $TI^{GDP}_{imp,exp} = TI_{imp,exp}/\left(GDP_{imp} + GDP_{exp}\right)$. Then the measure is multiplied by the exporter country's R&D to consider the technology component of trade flows. That yields the R&D-weighted trade intensity: $TI^{R\&D}_{imp,exp} = TI^{GDP}_{imp,exp} \times \%R\&D^{GDP}_{exp}$.

Because part of the imports represents "traditional" goods that do not necessarily carry any technology, we differentiate between the intensive margin and extensive margin of trade. Comin and Mestieri (2010) and Comin and Hobijn (2010) arrive at the conclusion that the intensive margin is more important to understand cross-country differences in adoption patterns and variations in productivities. Here, we adopt this conclusion by assuming that the intensive margin of adoption contributes more to the global R&D spillover.[13] Specifically, we denote $EM_{imp,exp}$ as the extensive

[11]See Keller (2004) for a comprehensive literature.

[12]Comin and Hobijn (2010) test the beneficial effect of foreign R&D on domestic productivity. Similarly, their measure of foreign R&D represents the knowledge embodied in the trade of intermediate goods used in domestic production.

[13]The economic meaning of the "intensive and extensive margin of adoption" is defined in the literature (e.g., Comin and Mestieri, 2010), and we paraphrase as follows: "the extensive margin of technology adoption gauges how long it takes for a country to adopt a technology. It determines the lag with which production methods arrive in a country. The intensive margin of adoption captures how many units of the good are demanded relative to aggregate demand once a technology has been introduced. It is determined by the productivity and price of goods that embody the technology and the cost that individual producers face in learning how to use it."

margin of trade, which is the variety of different products that country *exp* exports to country *imp*. The R&D-adjusted intensive margin is

$$IM^{R\&D}_{imp,exp} = \frac{\widehat{TI}^{R\&D}_{imp,exp}}{\widehat{EM}_{imp,exp}}, \tag{3}$$

where we take normalization for both the numerator and denominator to correct for the effect of trade openness; that is[14]

$$\widehat{TI}^{R\&D}_{imp,exp} = \frac{TI^{R\&D}_{imp,exp}}{\sum_{j=1}^{N} TI^{R\&D}_{imp,exp}}, \qquad \widehat{EM}_{imp,exp} = \frac{EM_{imp,exp}}{\sum_{j=1}^{N} EM_{imp,j}}, \tag{4}$$

where N is the number of countries in our sample.

Lastly, we use the R&D-weighted intensive margin to compute a concentration measure that resembles the Herfindahl-Hirschman Index (HHI),

$$TD_{imp} = \left[\sum_{exp=1}^{N} \left(IM^{R\&D}_{imp,exp} \right)^2 \right]^{1/2}, \text{ for } imp = 1, \ldots, N \quad . \tag{5}$$

The measure captures the cross-country diffusion of technology embedded in the quantity of trade per intermediate good. The measure accounts for the allocation of knowledge in the import flows between trade partners. [15] We compute this measure for each country *imp* at time t and call it the *tech-diffusion index*. Essentially, the index is the *R&D-adjusted import concentration in the intensive margin*. Intuitively, a high tech-diffusion measure implies that a country is central to the global R&D flow, while a low tech diffusion indicates that the country is peripheral to the global R&D flow. Our hypothesis is that high-interest-rate countries exhibit a higher concentration of technology diffusion because they receive more knowledge by importing R&D goods from their trade partners. On the contrary, low-interest-rate countries take on R&D themselves and export a

[14] Coe and Helpman (1995) find that the beneficial effect of foreign R&D spending on domestic productivity is stronger for countries more open to trade. The evidence in Comin and Hobijn (2004) also indicates that the degree of trade openness is among one of the most important determinants of the speed at which a country adopts technologies. We try to control for this effect when constructing our measure.

[15] We assign a higher value of tech diffusion to an importer that specializes in importing goods from a single country than another importer that diversifies the imports to multiple trade partners.

large quantity of high-technology goods to the high-interest-rate countries.

Tech-Diffusion-Sorted and Carry Trade Portfolios. We construct a currency risk factor based on the tech-diffusion measure and consider its relationship with the carry trade returns. First, at the end of each month t in year y, we allocate currencies into quintile portfolios based on the tech diffusion in year y-1. The first portfolio contains countries with a low concentration of R&D imports, and the last portfolio consists of currencies with a high concentration of R&D imports. The currency excess returns within each portfolio are equally weighted. We consider a zero-cost strategy that goes long in the last and short in the first portfolio and call it the *tech-diffusion factor*. Following Lustig et al. (2011a), we also consider a carry trade strategy based on the previous-month forward spread. The first basket contains currencies with the lowest forward discount and is named *funding currencies*, while the last basket consists of high-forward-discount currencies and is called *investment currencies*. The spread of currency returns between the first and the last portfolios is the carry trade excess return.

3 Baseline Empirical Results

This section presents the main empirical results. First, we discuss the relationship between technology diffusion, productivity risk exposure, and the currency risk premium. Then we include the tech diffusion into a two-factor asset-pricing model to consider its predicting ability for the cross-sectional currency excess returns. Lastly, we consider the implication of tech-diffusion index on unconditional carry trade returns.

3.1 Tech Diffusion and Interest Rate Differentials

Figure 1 illustrates how the constructed tech-diffusion measure is related to the currency risk premium. We plot the countries' average tech-diffusion measures against the average forward discounts in our sample. Overall, we find a strong positive correlation: the countries that adopt more R&D through international trade tend to have higher interest rates than countries that export R&D goods. Comparing the upper and lower panels shows that the relationship is stronger for the group of G10 currencies than the currencies of OECD countries. The fitted line in the bottom panel of figure 1 has a more significant slope coefficient and a larger R^2 than the line in the top panel.

A natural question is whether the interest rate spreads between the high- and low-tech-diffusion countries lead to a carry trade return. The answer is yes from figure C.1 in appendix C. Countries that adopt technologies through the intensive margin of trade (e.g., Australia and New Zealand) tend to generate a positive excess return against the U.S. dollar ($rx^j > 0$). On the other hand, countries that actively conduct innovations (e.g., Japan and Germany) tend to have negative currency excess returns in the carry trade portfolio ($rx^j < 0$). From the lower panel of figure C.1, we also find that the spread of currency excess returns is not completely driven by expected inflation. On average, the high-tech-diffusion countries enjoy a higher real interest rate ($r^j - r^{US} > 0$) than the low-tech-diffusion countries ($r^j - r^{US} < 0$).

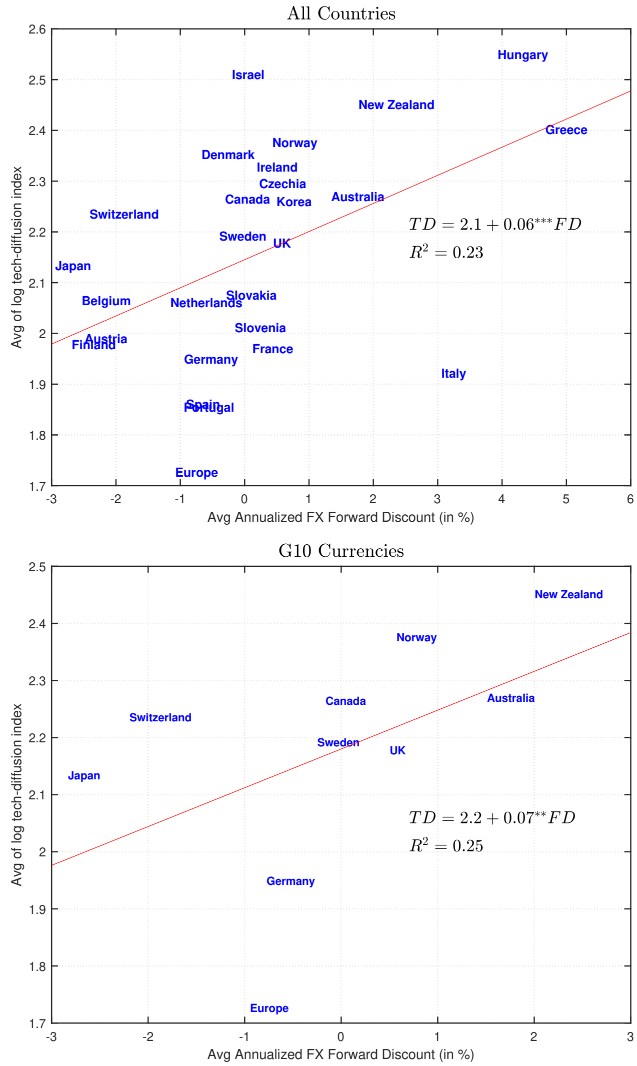
To test the significance of the relationship between technology diffusion and currency returns, we run a list of cross-sectional regressions based on Fama and MacBeth (1973). Specifically, in each month t of the calendar year y, we run the following cross-sectional regression:

$$rx_{i,t+1} = \alpha_t^r + \beta_t^r td_{i,y-1} + \gamma_t^r X_{i,y-1} + \varepsilon_{i,t+1}^r, \tag{6}$$

$$fd_{i,t} = \alpha_t^f + \beta_t^f td_{i,y-1} + \gamma_t^f X_{i,y-1} + \varepsilon_{i,t}^f. \tag{7}$$

Then we take the average of the estimated coefficients across time. $rx_{i,t+1}$ is the U.S. dollar-denominated return for investing in currency i from time t to time $t+1$. $fd_{i,t} = f_t^i - s_t^i$ is the currency-i's (log) forward discount at time t. The explanatory variable is the log tech-diffusion measure (td), while we also control for the share of GDP, the annualized inflation, and the trade-to-GDP ratio. The realized inflation is calculated as the percentage change in the consumer price index (CPI) over the previous year. We include the GDP share to control for the country size effect as in Hassan (2013). In our case, larger economies tend to be the ones making innovations and having a low-tech-diffusion measure. We also include the trade-to-GDP ratios in the regression to control for trade openness. Since part of the independent variables is reported annually, in our

Figure 1: Average Tech-Diffusion Index and Forward Discounts



Notes: The graph displays the average tech-diffusion indexes (TD) for our sample countries against the annualized forward discounts (FD). The upper panel reports results for "All Countries," while the bottom panel shows the pattern of "G10 Currencies."

specifications, we regress excess returns (or forward discounts) on independent values at the year y-1. We use Newey and West (1987) standard errors that are corrected for heteroskedasticity and autocorrelation. This approach allows us to consider the cross-sectional inference for the effect of technology transmission on currency risk premia.

Panel A of table 2 shows the regression results for the excess returns, and panel B shows the results for the forward discounts. The left-hand side of each panel shows the estimation for OECD

Table 2: Cross-Sectional Regressions of Excess Returns and Forward Discounts

	Panel A: Fama-MacBeth Regression of FX Ret: rx_{t+1}							
	All Countries				**G10 Currencies**			
Tech Diffusion	0.28***	0.24***	0.32**	0.31***	0.38***	0.27*	0.29*	0.29
	(0.11)	(0.07)	(0.13)	(0.11)	(0.14)	(0.15)	(0.18)	(0.19)
CPI-Inflation		7.89**		6.27		9.48		4.72
		(3.68)		(3.89)		(6.04)		(7.91)
GDP Share			-0.39	-0.15			-1.85	-1.89
			(0.99)	(0.74)			(1.13)	(1.43)
Trade-to-GDP			0.13	0.03			-0.34	-0.24
			(0.18)	(0.13)			(0.23)	(0.33)
Cons.	-0.55**	-0.60**	-0.91**	-0.80**	-0.81***	-0.63**	-1.28***	-1.40***
	(0.26)	(0.25)	(0.35)	(0.31)	(0.29)	(0.31)	(0.49)	(0.52)
Adj. R^2	0.06	0.19	0.26	0.38	0.11	0.30	0.46	0.60
No. of Obs.	4,636	4,636	4,636	4,636	2,795	2,795	2,795	2,795
	Panel B: Fama-MacBeth Regression of Fwd Dsct: fd_t							
Tech Diffusion	0.29***	0.20***	0.25**	0.17**	0.31***	0.29***	0.23***	0.27***
	(0.07)	(0.04)	(0.11)	(0.08)	(0.05)	(0.04)	(0.06)	(0.05)
CPI-Inflation		6.53***		6.69***		8.77***		4.80***
		(0.93)		(0.94)		(1.26)		(1.62)
GDP Share			-0.86	-0.66*			-1.83***	-1.37***
			(0.54)	(0.38)			(0.39)	(0.29)
Trade-to-GDP			-0.05	-0.12***			-0.38***	-0.30***
			(0.07)	(0.03)			(0.11)	(0.09)
Cons.	-0.60***	-0.54***	-0.85***	-0.68***	-0.67***	-0.77***	-1.11***	-1.12***
	(0.16)	(0.10)	(0.25)	(0.16)	(0.13)	(0.09)	(0.16)	(0.09)
Adj. R^2	0.19	0.47	0.34	0.58	0.19	0.55	0.70	0.81
No. of Obs.	4,648	4,648	4,648	4,648	2,795	2,795	2,795	2,795

Notes: This table presents cross-sectional Fama and MacBeth (1973) regressions of log excess returns (rx: panel A) and log forward discounts (fd: panel B) on tech diffusion (in logs) and a list of control variables that includes the GDP share, annualized CPI inflation, and trade-to-GDP ratio. Figures in parentheses are Newey and West (1987) standard errors corrected for heteroskedasticity and autocorrelation (HAC) using 36 lags. Since some independent variables are calculated annually, for each regression, the forward discount and returns are regressed on the regressor values in the calendar year y-1, where y is the calendar year of the monthly observation. The currency data are collected from Datastream *via* Barclays and Reuters and contain monthly series from January 1993 to December 2019. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

countries, while the right-hand side shows results for G10 currencies. Overall, it is evident that tech diffusion positively correlates with future excess returns and contemporaneous forward discounts. The magnitude of the effect is comparable between the two samples. On average, a 1% increase in our tech-diffusion measure induces a 0.3% percent increase in the currency excess return and a 0.25% increase in the forward discount. The effect of tech diffusion on the forward discount is more significant than the effect on excess return since exchange rate fluctuations are largely unpredictable. In addition, the result still holds after we control for the country size, inflation, and trade openness. The point estimate also suggests that larger economies tend to have lower currency returns and interest rates, which is consistent with the result of Hassan (2013).

A comparison across different specifications shows that CPI inflation has a significant and positive impact on the forward premium. Its effect on currency returns is also positive but less significant. Adding factors such as GDP share and trade openness into the model induces a higher R^2 in the regression. Together with these two variables, our tech-diffusion measure explains a substantial portion of the cross-sectional variation in the forward discounts and currency excess returns (from 26% to 70%). Most importantly, the inclusion of GDP share and inflation does not significantly alter the predictive power of tech diffusion in the cross-sectional regressions, although the coefficients of these two variables are also significant in some specifications.

3.2 Tech Diffusion and Global Risk Exposure

The relationship between tech diffusion and interest rate differentials leads us to think about the economic mechanism behind it. Lustig and Verdelhan (2007) show that investors' exposure to aggregate consumption risk can account for the violation of the UIP condition and explains the return difference between high-interest-rate and low-interest-rate currency portfolios. Colacito et al. (2018) build an endowment economy with recursive preference to show that FX carry trade strategy à la Lustig et al. (2011a) can be explained by countries' heterogeneous exposure to a long-run global growth shock. Almost at the same time, other papers provide microfoundations to this heterogeneous risk exposure and suggest that the spread of interest rates across countries can be attributed to their different specialties in the production technologies (i.e., Ready et al., 2017) or different positions in the global trade network (i.e., Richmond, 2019). In this subsection, we consider how the spillover of R&D helps to account for heterogeneous risk exposure.

Figure 2 plots the risk exposure against the average (log) tech-diffusion measure. To derive the productivity risk exposure for each country (β_i^z), we run the following time-series regression:

$$\Delta\text{Productivity}_{i,t} = \alpha_i^z + \beta_i^z \times \Delta\text{World Productivity}_t + \varepsilon_{i,t}^z \ .$$

where $\text{Productivity}_{i,t}$ is the country-level labor productivity at time t and $\text{World Productivity}_t$ is the measure of world productivity from the WDI database. To calculate the consumption risk exposure (β_i^z), we replace the independent variable with the simple average of consumption growth across countries. It is clear from figure 2 that low-tech-diffusion countries (such as Portugal, France, and Finland) tend to have a stronger comovement with the global business cycle, while high-tech-diffusion countries (such as Norway, New Zealand, and Hungary) are less exposed to global shocks. Moreover, a comparison between upper and lower panels indicates that the impact of tech diffusion on risk exposure is stronger if we use productivity growth in the regression rather than consumption growth. [16]

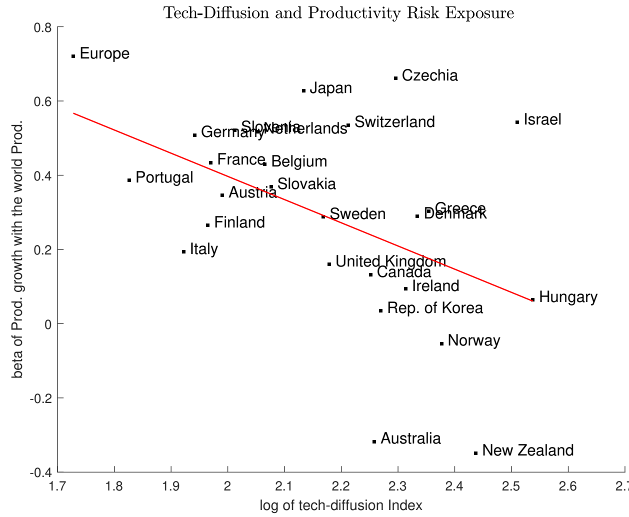
To consider whether this relationship is quantitatively important, tables B.1-B.2 in appendix B regress the productivity (or consumption) growth betas on our tech-diffusion measures. We find that the cross-sectional difference in tech diffusion can explain the heterogeneity in risk exposure even after we control for the country size, trade openness, and R&D volume. Adopting technologies through imports allows the high-interest-rate countries such as Australia, New Zealand, and Norway to hedge against global productivity shocks.

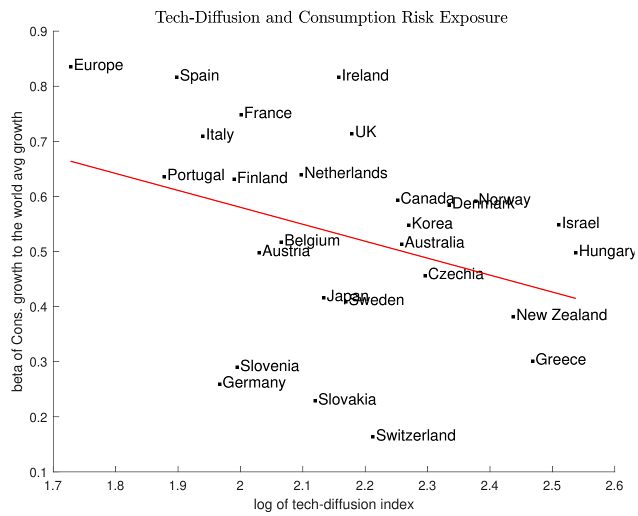
How does the heterogeneous risk exposure account for the abovementioned asset-pricing implications? Figure 3 plots the time paths of productivities, the real exchange rates, and interest rate differentials for a typical pair of high- and low-interest-rate countries: Australia versus Japan. [17] Relative productivity is defined as the log difference in labor productivities between Australia and Japan. For a particular country, the real exchange rate (against the U.S. dollar) is the nominal exchange rate adjusted by the country's relative CPI levels. The relative real exchange rate is the log difference in the real exchange rates between two countries. The increase in the number indicates a real depreciation of the Australian dollar against the Japanese yen. The real interest rate is calculated using the three-month forward discount subtracted by the four-quarters moving average of inflation.

[16] Figures C.2-C.4 in appendix C show that a similar pattern holds for a broader set of countries or if we replace the risk exposure measure with countries' consumption risk exposure to the U.S. economy.

[17] Japan is Australia's second-largest trading partner aside from the eurozone. Since the productivities are heterogeneous among the eurozone member countries, it is difficult to find a direct link between productivity risk exposure and currency excess return if we treat the eurozone as an integrated economy. So we use Australia versus Japan, New Zealand versus Japan, and Norway versus Japan as three pairs of high- and low-interest-rate countries to illustrate the mechanism.

Figure 2: Tech-Diffusion Index and Heterogeneous Risk Exposure

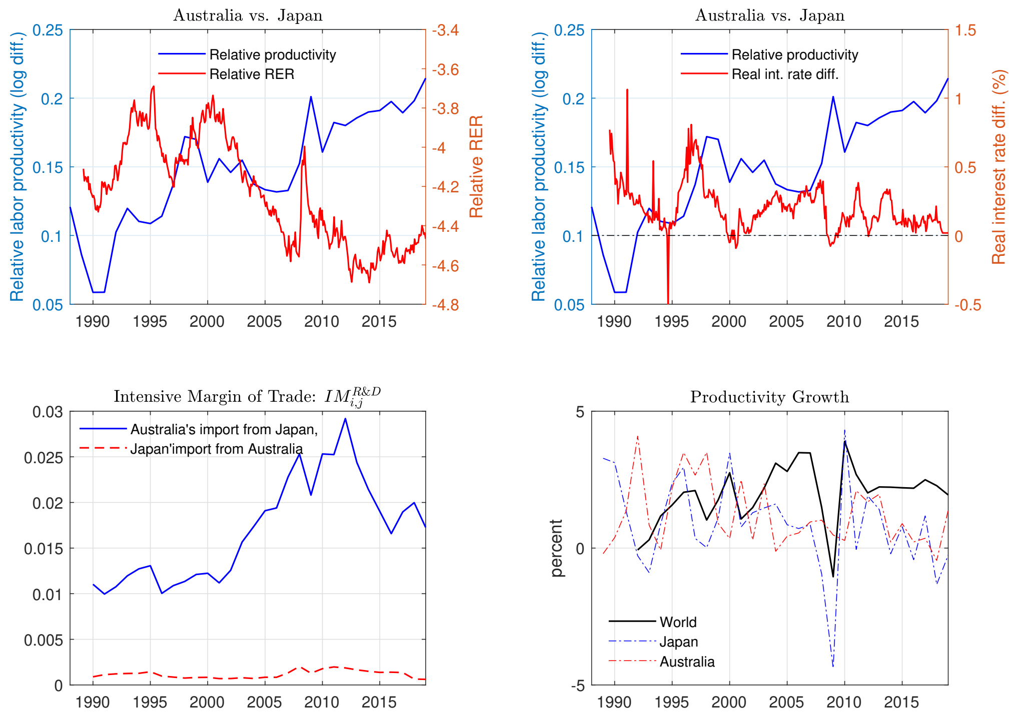




Notes: The figure plots the productivity growth (β_i^z) or consumption growth betas (β_i^c) for our sample countries against their average tech-diffusion measures (TD). A country's productivity growth beta is calculated by regressing the country-level productivity growth on the world productivity growth. To calculate the consumption growth beta, we regress a country's consumption growth rate on the average growth rate across countries.

From the bottom right panel of figure 3, we find that Japan has a stronger comovement with global productivity shocks than Australia. Australia's smaller risk exposure indicates that its relative productivity is higher during the Global Financial Crisis of 2008 (the blue line in the upper panels). The increased relative productivity depreciates the Australian dollar against the Japanese yen in the downturn (upper left panel). In the upper right panel, we notice that the real interest rates are, on average, higher in Australia than in Japan. Apart from that, during the financial

Figure 3: Relative Productivity, Real Exchange Rate, and Interest Rate Differentials: Australia versus Japan



Notes: The figure shows the time series of productivities, relative real exchange rates, real interest rate differentials, and R&D content of imports (intensive margin) for a pair of high- and low-tech-diffusion countries. In the bottom left panel, the classification of high-technology goods is based on the UN's SITC code of manufactured products. Australia is considered a high-tech-diffusion country, while Japan is Australia's major trading partner aside from the eurozone.

crisis, the expected appreciation of the Australian dollar lowered Australia's interest rate by more than the interest rate in Japan. Overall, we find that Australia's relative real exchange rate against the Japanese yen is procyclical (appreciates in good times and depreciates in bad times), the same as their interest rate differentials.

The lower left panel shows the R&D content of bilateral trade between these two countries (R&D-adjusted intensive margin of trade). We notice that Australia imports more technology goods from Japan than Japan imports from Australia. Moreover, the R&D import from Japan to Australia experienced years of fast growth in the period proceeding the Global Financial Crisis until it encountered a sudden stop. Figures C.5-C.6 in appendix C show that the same mechanism applies to other country pairs such as New Zealand versus Japan or Norway versus Germany.

In sum, the heterogeneous global shock exposure generates distinct risk profiles for different currencies and produces a spread of interest rates. The fact that high-tech-diffusion currencies depreciate during the downturn makes them a negative hedge from international carry traders' perspective, causing a risk premium. Meanwhile, high-tech-diffusion countries' smaller exposure to business cycle risk alleviates domestic agents' precautionary saving motive and raises their domestic interest rate. In section 5, we will integrate these channels in a two-country production economy and characterize the relationship between risk premia and technology diffusion.[18]

3.3 Descriptive Statistics of Portfolio Returns

To examine the predicting power of tech diffusion on the forward discount and currency returns, in this section, we sort currencies into five portfolios based on the previous-year tech-diffusion index. We use this specification because the trade data from the UN Comtrade is reported with a time delay. Following Lustig et al. (2011a), we construct the carry trade portfolio using the previous-month forward spread.

In particular, we denote $rx^i_{t+1} = f^i_t - s^i_{t+1}$ as the log excess return of currency i (against the U.S. dollar) from time t to $t+1$. The excess return of portfolio j is given by $rx^j_{t+1} = \sum_{i \in N_j} rx^i_{t+1}/N_j$, where N_j represents the number of currencies in that portfolio. Similarly, we denote $RX^i_{t+1} = \left(F^i_t - S^i_{t+1}\right)/S^i_t$ as currency i's excess return in level, and the corresponding excess return of portfolio j is $RX^j_{t+1} = \sum_{i \in N_j} RX^i_{t+1}/N_j$. In the main text, we consider the construction of portfolios before transaction costs. Since the tech-diffusion measure requires annual rebalancing, the effect of transaction costs are likely to be small. [19]

Panel A of table 3 provides the summary statistics of quintile portfolios that are sorted on previous-year tech diffusion. The currencies in the first (last) portfolio represent 20% of the currencies having the lowest (highest) tech-diffusion measure in the previous year. The last column of each panel displays a zero-cost strategy that buys the high-tech-diffusion portfolio and sells the low-tech-diffusion one. From now on, this high-minus-low investment strategy is named *adoption-minus-*

[18] Using a structural model, in section 5, we show that the endogenous reallocation of resources between the innovation and adoption sectors allows a high-interest-rate country to smooth its business cycle, resulting in smaller exposure to global shocks.

[19] Table B.3 in appendix B displays the summary statistics of portfolio sorting after eliminating the bid-ask spread.

innovation (AMI), and we contrast it with the traditional FX carry trade strategy (HML^{FX}) in the following analysis.

First, we note that the currency portfolio of R&D exporter countries generates a negative forward discount on average, which means that these countries have lower interest rates than the U.S. In contrast, the portfolio of R&D adoption countries has positive forward discounts. The forward discount increases virtually monotonically from P_L to P_H, with a spread of 2.41% (2.48%) in the full sample (G10 currencies). Second, the spread in forward discounts fully translates into the spread in currency excess returns, which contradicts the UIP condition. For both the OECD sample and the G10 currencies, investing in the high-tech-diffusion currencies delivers a positive excess return. The opposite is true for investing in low-tech-diffusion currencies. The spread of Sharpe ratios between the high and low portfolios is slightly above 0.4. Lastly, the same monotone pattern applies to the real interest rate differentials. High-tech-diffusion countries tend to have a higher real interest rate than the low-tech-diffusion economies. [20] This indicates that the spread of forward discounts is not entirely driven by the expected inflation channel.

[20] Both the spread in forward discounts and the spread in real interest rates between the high and low portfolios are statistically significant at the 1% level. Their t-statistics are omitted in the table.

Table 3: Summary Statistics of Currency Portfolios

	P_L	P_2	P_3	P_4	P_H	HML	P_L	P_2	P_3	P_4	P_H	HML
Panel A: Sorted on Technology Diffusion												
	All Countries						**G10 Currencies**					
	Log Excess Returns: rx^j						Log Excess Returns: rx^j					
Mean	-0.85	0.47	-0.14	1.60	1.97	2.82	-1.74	-0.39	1.20	0.46	1.76	3.50
	[-0.47]	[0.26]	[-0.08]	[0.87]	[0.95]	[2.46]	[-0.94]	[-0.23]	[0.52]	[0.27]	[0.84]	[2.51]
	Arithmetic Excess Returns: RX^j						Arithmetic Excess Returns: RX^j					
Mean	-1.30	-0.06	-0.71	1.07	1.37	2.67	-2.25	-0.88	0.61	-0.04	1.16	3.41
Sdev	8.06	8.67	8.92	8.96	9.56	6.36	8.50	8.62	10.92	8.72	9.73	7.92
SR	-0.16	-0.01	-0.08	0.12	0.14	0.42	-0.26	-0.10	0.06	-0.00	0.12	0.43
	Forward Discount: $f^j - s^j$						Forward Discount: $f^j - s^j$					
Mean	-0.39	-0.31	0.14	0.62	2.02	2.41	-1.19	-0.47	0.43	0.38	1.29	2.48
	Real Int. Rate Diff.: $r^j - r^{US}$						Real Int. Rate Diff.: $r^j - r^{US}$					
Mean	0.08	0.33	0.40	0.79	1.62	1.55	-0.19	0.34	0.87	0.78	1.67	1.87
	Exposure to World Prod.: β^z_j						Exposure to World Prod.: β^z_j					
Corr	0.41	0.41	0.29	0.20	0.15	-0.26	0.60	0.41	0.15	0.03	-0.13	-0.73
Panel B: Sorted on Forward Discounts												
	Log Excess Returns: rx^j						Log Excess Returns: rx^j					
Mean	-1.83	-0.61	1.42	0.60	3.17	5.00	-1.73	-1.28	1.40	-0.07	2.97	4.70
	[-1.04]	[-0.33]	[0.83]	[0.31]	[1.41]	[3.05]	[-1.01]	[-0.71]	[0.72]	[-0.04]	[1.31]	[2.35]
	Arithmetic Excess Returns: RX^j						Arithmetic Excess Returns: RX^j					
Mean	-2.39	-1.07	0.98	0.07	2.47	4.86	-2.26	-1.71	0.99	-0.60	2.29	4.55
Sdev	8.45	8.68	8.24	8.94	10.73	8.05	8.57	8.30	9.17	9.34	10.90	10.00
SR	-0.28	-0.12	0.12	0.01	0.23	0.60	-0.26	-0.21	0.11	-0.06	0.21	0.46
	Forward Discount: $f^j - s^j$						Forward Discount: $f^j - s^j$					
Mean	-1.90	-0.67	0.01	1.03	3.53	5.43	-2.27	-0.73	-0.01	0.72	2.46	4.72
	Real Int. Rate Diff.: $r^j - r^{US}$						Real Int. Rate Diff.: $r^j - r^{US}$					
Mean	-0.58	-0.22	0.40	1.13	2.50	3.09	-0.55	-0.08	0.51	0.94	2.47	3.02
	Exposure to World Prod.: β^z_j						Exposure to World Prod.: β^z_j					
Corr	0.49	0.40	0.28	0.11	-0.06	-0.55	0.55	0.39	0.20	0.04	-0.22	-0.77

Notes: This table presents the summary statistics of quintile currency portfolios sorted on the tech-diffusion measure (panel A) and forward discount (panel B). The first (last) portfolio P_L (P_H) comprises 20% of all currencies with the lowest (highest) value of tech diffusion or forward discount. HML is a long-short strategy that buys P_H and sells P_L. The table presents the annualized mean, standard deviation (in percentage points), and Sharpe ratios. We also report the forward discounts, real interest rate differentials, and productivity risk exposure of each portfolio. Figures in square brackets represent Newey and West (1987) t-statistics corrected for heteroskedasticity and autocorrelation (HAC) using the optimal number of lags. The data are collected from Datastream *via* Barclays and Reuters and contain monthly series from January 1993 to December 2019.

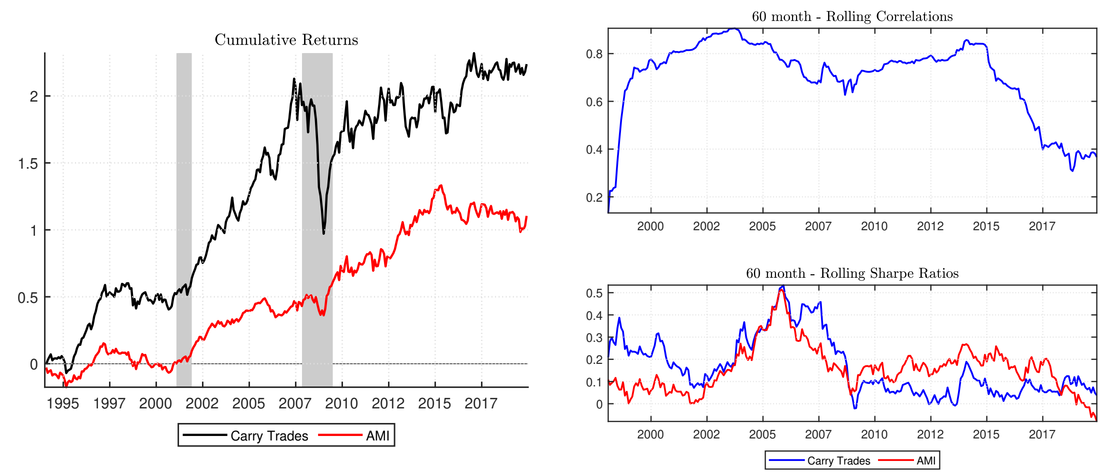
One thing to note is that the difference in excess returns between P_H and P_L (2.82% and 3.50%) is higher than the difference in forward discounts (2.41% and 2.48%), which implies that the high-tech-diffusion currencies tend to appreciate in the future and the low-tech-diffusion currencies tend to depreciate. The last line of each panel in table 3 shows the countries' average risk exposure in each portfolio. It appears that countries in the high-tech-diffusion basket always enjoy the lowest risk exposure.

Panel B of table 3 reports the statistics of carry trade portfolios. We find that both currency excess return and forward discount follow similar patterns as the tech-diffusion-sorted portfolios. The spread in the average forward discount is larger than the spread in the AMI strategy, which is not surprising since the forward discount is the source of variation for these portfolios. The excess returns also rise monotonically from P_L to P_H. In both samples, the spread of forward discounts fully translates into the spread of excess returns with the same magnitude, implying that the interest rate may contain more information than the future exchange rate fluctuations. The conditional carry strategy of buying high-interest-rate currencies and selling low-interest-rate currencies renders a Sharpe ratio of 0.6 or 0.48, higher than those from the AMI strategy. The last line of panel B shows that countries with the highest forward discount (or the highest real interest rate) have the lowest productivity risk exposure.

Cumulative Returns and Rolling Statistics. One key difference between the carry and tech-diffusion strategies is that, in the former case, the spread of forward discounts is higher than the spread of excess returns. But the opposite is true for the tech-diffusion strategy. This suggests that the tech diffusion may contain additional information about the risk premium rather than the forward discount.[21] Figure 4 provides a visual comparison of these two strategies. The left panel shows cumulative returns of the carry trade and tech-diffusion portfolios, and the right panel shows their (60-month) rolling-window correlations and the Sharpe ratios. We find that the carry trade strategy was very profitable until the Global Financial Crisis of 2008, when the payoff became flat

[21] Figures C.10-C.13 in appendix C compares the portfolio turnover rates between the carry trade strategy and tech-diffusion strategy. Although the two sorting strategies do not completely overlap, the countries in the extreme baskets are almost identical. However, exceptions do exist. For example, the Swiss franc is considered a low-interest-rate currency in the carry trade strategy, but Switzerland is not categorized as a low-tech-diffusion economy.

Figure 4: Cumulative Returns and Rolling-Window Statistics

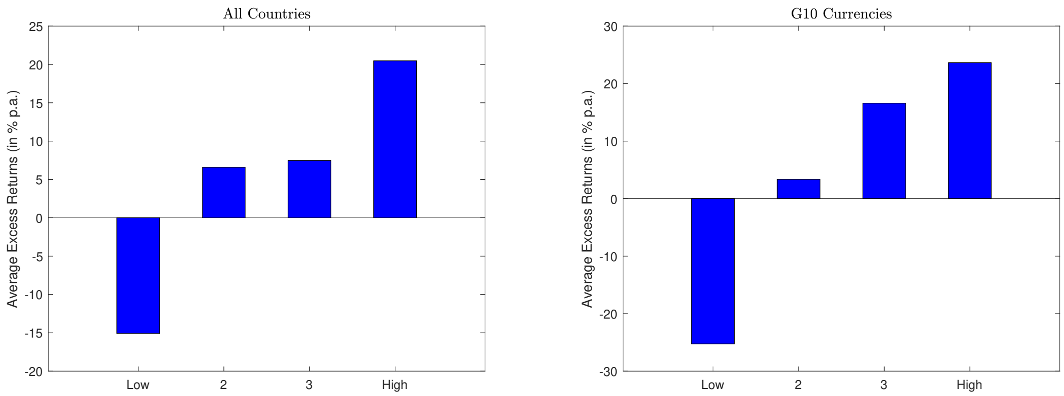


Notes: The left panel displays the cumulative returns from the carry trade and tech-diffusion-sorted (AMI) portfolios. The right panel displays (60-month) rolling-window correlations of the carry and AMI portfolios as well as their rolling-window Sharpe ratios. The data contain monthly series from January 1993 to December 2019. The results are based on the group of G10 currencies.

afterward. The cumulative return based on the AMI factor is much smaller due to the annual rebalancing, but it exhibits a similar pattern to the carry trade. In the right panel, we find that the correlation between carry and AMI factors quickly rose up to 80% after 2000 but declined sharply in 2015. The rolling Sharpe ratios of the two strategies are closely connected. For both strategies, the Sharpe ratios are relatively higher in the period of 2002 to 2008 than in the post-2008 episode. Even though the carry trade strategy is more profitable, its larger volatility renders a similar Sharpe ratio to our AMI strategy.

To better understand the relationship between carry trades and technology diffusion, figure 5 provides a visual illustration of the carry trade profitability conditional on the technology diffusion level. Specifically, we divide the time series of the tech-diffusion factor (i.e., AMI) into quartiles so that the first (last) quartile represents a basket with the 25% lowest (highest) realizations of the factor over its sample distribution. Then, in each basket, we calculate the mean excess return between extreme quintiles for the interest-rate-sorted portfolios. In the end, each bar in figure 5 represents the average carry trade return under a specific state of technology diffusion. We observe a monotonic pattern of carry trade returns. This suggests that the profitability of carry trades strongly covaries with our tech-diffusion strategy. To put it another way, sorting currencies based

Figure 5: Carry Trade Conditional on Technology Diffusion



Notes: We first divide the time series of the AMI factor into quartiles so that the first (last) quartile represents a basket with the lowest (highest) tech-diffusion measure (TD). Then, in each basket of AMI realizations, we calculate the mean excess return between extreme quintiles for the interest-rate-sorted portfolios. Each bar represents the average carry trade return conditional on a specific tech-diffusion state.

on the measure of tech diffusion entails similar information to the forward discount.

3.4 Asset-Pricing Tests

This section performs cross-sectional asset-pricing tests and examines the pricing ability of the tech-diffusion factor for the carry trade portfolio returns. Following the methodology in Cochrane (2005), under the no-arbitrage condition, the excess return for any asset j satisfies the following Euler equation:

$$\mathbb{E}\left[\mathcal{M}_{t+1} RX^j_{t+1}\right] = 0, \tag{8}$$

where $\mathcal{M}_{t+1}$ is the U.S. investors' stochastic discount factor (SDF) that is to be projected on a list of risk factors. In our case, RX^j_{t+1} is the currency excess returns for portfolio j at time $t+1$. [22]

We assume the SDF takes a linear form: $\mathcal{M}_{t+1} = 1 - b'(\phi_{t+1} - \mu_\phi)$, where b represents the vector of factor loadings and μ_ϕ is the vector of factor means; that is, $\mu_\phi = \mathbb{E}(\phi_{t+1})$. Then, we can derive the beta representation of the asset-pricing model:

$$\mathbb{E}\left[RX^j\right] = \lambda' \beta^j. \tag{9}$$

[22] We use excess returns in levels instead of logs in the asset-pricing tests so as to avoid having to assume the joint log-normality of returns and the pricing kernel.

Equation (9) says that the expected excess return of portfolio j equals the factor price λ multiplied by the risk exposure of this portfolio β^j. The vector of factor price is expressed as $\lambda = \Sigma_\phi b$, where $\Sigma_\phi = E[(\phi_{t+1} - \mu_\phi)(\phi_{t+1} - \mu_\phi)']$ represents the variance-covariance matrix of the risk factors. The beta of each portfolio (β^j) can be derived by running a time-series regression of the portfolio excess return (rx^j_{t+1}) on risk factors (ϕ_{t+1}).

We use two methods to jointly estimate factor prices λ and portfolio betas β, together with the factor loadings (b), factor means (μ), and variance-covariance matrix (Σ_ϕ). The first method is based on the linearization of the generalized method of moments (GMM) as introduced by Hansen (1982). Since the main purpose of this study is to examine the pricing ability of the model on the cross-section of currency returns, we restrict our attention to unconditional moments with no instruments apart from a constant. In the first stage of the GMM (referred to as GMM_1), we start with an identity weighting matrix to see whether the factors can price the cross-section of the currency excess returns equally well. In the second stage (referred to as GMM_2), we choose the optimal weighting matrix by minimizing the difference between the objective functions under heteroskedasticity- and autocorrelation-consistent (HAC) estimates of the long-run variance-covariance matrix of the moment conditions. The estimation of the variance matrix is based on Newey and West (1987) and uses the optimal number of lags.

In the second method, we perform a two-stage OLS estimation based on Fama and MacBeth (1973) (hereafter FMB). In the first stage, we run a time-series regression of portfolio returns on risk factors to get their betas. In the second stage, we run a cross-sectional regression of the portfolios' average excess returns on the betas, period by period (without an intercept term). The factor price λ is the average of the slope coefficients in the cross-sectional regression. We report both Newey and West (1987) as well as Shanken (1992) standard errors to account for the potential "errors-in-variables" issue.

Cross-Sectional Analysis. Lustig et al. (2011a) show that the traditional carry trade portfolios are characterized by heterogeneous exposure to a common risk factor – the slope factor. The high-interest-rate currencies load more on this slope factor than the low-interest-rate currencies. The purpose of our analysis is to show that our tech-diffusion measure can capture the bulk proportion

Table 4: Cross-Sectional Asset-Pricing: DOL and AMI factors

Panel A: Factor Prices

	λ_{DOL}	λ_{AMI}	χ^2	R^2	$RMSE$	λ_{DOL}	λ_{AMI}	χ^2	R^2	$RMSE$
	All Countries					**G10 Currencies**				
GMM_1	0.18	8.31	3.63	0.69	0.69	−0.22	6.22	5.17	0.52	0.92
	(1.81)	(3.93)	{0.30}			(1.82)	(2.84)	{0.16}		
GMM_2	0.19	9.37	3.56			−0.22	7.53	5.04		
	(1.80)	(3.90)	{0.31}			(1.79)	(3.04)	{0.17}		
FMB	0.16	8.17	5.00			−0.22	6.12	5.23		
(NW)	(1.56)	(2.67)	{0.29}			(1.53)	(2.61)	{0.26}		
(Sh)	(1.56)	(2.82)				(1.53)	(2.65)			

Panel B: Factor Betas

	α	β_{DOL}	β_{AMI}	R^2		α	β_{DOL}	β_{AMI}	R^2
P_L	−0.20	0.95	−0.27	0.78	P_L	−0.19	0.88	−0.40	0.65
	(0.06)	(0.05)	(0.09)			(0.08)	(0.07)	(0.08)	
P_2	−0.09	0.99	−0.13	0.83	P_2	−0.14	0.92	−0.13	0.72
	(0.05)	(0.05)	(0.06)			(0.06)	(0.05)	(0.05)	
P_3	0.08	0.95	−0.05	0.84	P_3	0.08	0.87	0.08	0.59
	(0.05)	(0.03)	(0.05)			(0.09)	(0.06)	(0.05)	
P_4	0.01	0.99	0.08	0.83	P_4	−0.05	1.00	0.17	0.80
	(0.06)	(0.04)	(0.08)			(0.06)	(0.05)	(0.05)	
P_H	0.21	1.16	0.27	0.85	P_H	0.19	1.16	0.25	0.82
	(0.07)	(0.04)	(0.10)			(0.07)	(0.04)	(0.07)	

Notes: This table reports asset-pricing results for the two-factor model that comprises the DOL and AMI risk factors. We use as test assets five currency portfolios sorted based on past forward discounts (i.e., carry trade portfolios). We rebalance the portfolios on a monthly basis. Panel A reports GMM_1, GMM_2, and the Fama and MacBeth (1973) estimates of the factor prices (λ). We also display Newey and West (1987) standard errors (in parentheses) corrected for autocorrelation and heteroskedasticity with optimal lag selection. Sh are the corresponding values of Shanken (1992). The table also shows χ^2 and cross-sectional R^2. The numbers in curly brackets are *p-values* for the pricing error test. Panel B reports OLS estimates of contemporaneous time-series regressions with HAC standard errors in parentheses. The alphas are annualized. We do not correct for transaction costs, and excess returns are expressed in percentage points. The currency data are collected from Datastream *via* Barclays and Reuters and contain monthly series from January 1993 to December 2019.

of this global risk factor and account for most of the cross-sectional variation in carry trade excess returns. We assume a two-factor model with the following form:

$$\mathcal{M}_{t+1} = 1 - b_{DOL}\left(DOL_{t+1} - \mu_{DOL}\right) - b_{AMI}\left(AMI_{t+1} - \mu_{AMI}\right), \tag{10}$$

where DOL represents the level (dollar) factor that buys market currencies and sells the U.S. dollar. AMI is the slope factor of our interest that captures the heterogeneous exposure to the state of technology transmission.

Panel A of table 4 shows the results of the cross-sectional asset-pricing tests: the estimation of factor prices (λ), the test of pricing errors (χ^2), the cross-sectional R^2, and the root-mean-square error. [23] The left panel shows the results of the OECD countries, while the right panel is only for G10 currencies. From the estimation, we find that the price of the tech-diffusion factor (λ_{AMI}) is always positive and statistically significant based on HAC and Shanken (1992) standard errors. The t-statistics of λ_{AMI} are roughly the same under the GMM method and under Fama and MacBeth (1973) (3.05 in the full sample and 2.34 for the G10 currencies). Moreover, the χ^2 tests suggest that the cross-sectional pricing errors are insignificant, indicating that our tech-diffusion factor is a key variable that explains the cross-sectional variation in currency excess returns. Regarding the goodness of fit of the model, we find a sizeable cross-sectional R^2, representing 69% in the full sample, and 52% using the sample of G10 currencies.[24]

One thing to note is that the estimate of the dollar factor price (λ_{DOL}) is negative in all specifications and statistically insignificant. This is due to the fact that global interest rates have largely been affected by the unconventional monetary policies that came into force after the Global Financial Crisis. These large-scale monetary easing programs greatly lowered currency returns in the market portfolio. Table B.6 in appendix B shows the asset-pricing tests separately on the samples before and after the Global Financial Crisis. We find that for both the OECD and G10 currencies, the price of the dollar factor (λ_{DOL}) becomes positive if we only use the sample before 2008. Moreover, the price of the slope factor (λ_{AMI}) is also more significant than the baseline results using the pre-2008 sample. In addition, table B.5 in appendix B shows asset-pricing results when we include both carry-trade-sorted and tech-diffusion-sorted portfolios as test assets to maximize the power of the tests. We notice that the estimate of factor price (λ_{AMI}) becomes smaller but more significant due to the reduced standard errors.

[23] The χ^2 statistics (together with the p-values) test the null hypothesis that all pricing errors in the cross-section are mutually equal to zero. The cross-sectional pricing errors are computed as the difference between the realized and predicted excess returns. Figure C.14 in appendix C displays the pricing error plots at the portfolio level. Our model generates a strong fit since most of the portfolios are closely aligned with the 45-degree line.

[24] Figure C.15 in appendix C shows the pricing error plots for the currency-level regressions. It is not surprising that the estimates are less precise than the portfolio-level regressions because the currency-level approach introduces more noise to the data. Most currencies are closely aligned with the 45-degree line except for some euro area currencies, such as Greece, Portugal, Spain, and Italy, which deviate from the 45-degree line due to their shorter samples. This is evident in the lower panel of figure C.15, where we can see that most of the G10 currencies are close to the 45-degree line.

Time-Series Analysis. Panel B of table 4 displays the coefficients of the time-series regressions in the first pass of Fama and MacBeth (1973) for each of the five currency portfolios. The coefficients on the dollar factor (DOL) are all close to one, indicating that all carry portfolios roughly have the same exposure to this level factor. More importantly, the betas on our tech-diffusion (AMI) factor increase in an almost monotonic fashion from the low-interest-rate to the high-interest-rate currencies. The slope coefficients for the extreme portfolios are highly significant, as indicated by the HAC standard errors. However, the difference in exposure between the high and low portfolios ($\beta^H_{AMI} - \beta^L_{AMI}$) is not equal to one, which indicates that our AMI factor only accounts for part of the cross-sectional variation in currency excess returns. The time-series R^2 ranges from 78% to 85% using the full sample and 65% to 82% using the G10 currencies.[25] Thus, this structure of portfolio betas provides us with evidence that the carry-trade-sorted portfolios are characterized by heterogeneous exposure to a common global risk factor that is related to international technology transmission.

3.5 Beta-Sorted Portfolios

Our baseline exercise in table 4 indicates that the forward-discount-sorted portfolios (carry) generate a structure of heterogeneous exposure to the global tech-diffusion risk. This section considers the opposite question: whether the portfolios sorted on tech-diffusion betas lead to the same monotone pattern of excess returns or interest rates. Specifically, in each date t, we regress the currency i's log excess return rx^i_t on a constant and AMI_t factor using a 36-month rolling window that ends in period t-1. [26] This gives rise to the currency i's exposure to the tech-diffusion factor in time t: $\beta^i_{AMI,t}$. Then we sort currencies into quintile portfolios in each period based on their sensitivity to the global risk factor. Portfolio 1 contains currencies with a negative exposure to the tech-diffusion factor, and portfolio 5 includes currencies with positive exposure. Table 5 reports the summary statistics of the beta-sorted portfolios. Panel A shows results for all countries, and Panel B displays

[25] Figure C.18 of appendix C provides an estimate of the time-varying factor price ($\lambda_{AMI,t}$) using a (36-month) rolling-window regression in the first stage of Fama and MacBeth (1973). The strong comovement between factor prices ($\lambda_{AMI,t}$) and the carry trade high-minus-low return (HML^{FX}_t) demonstrates the strong pricing ability of our tech-diffusion measure.

[26] Table B.4 in appendix B shows the beta-sorted portfolios when using a 24-month rolling windows in the time-series regressions.

Table 5: Portfolios Sorted on Tech-Diffusion Betas: 36-Month Windows

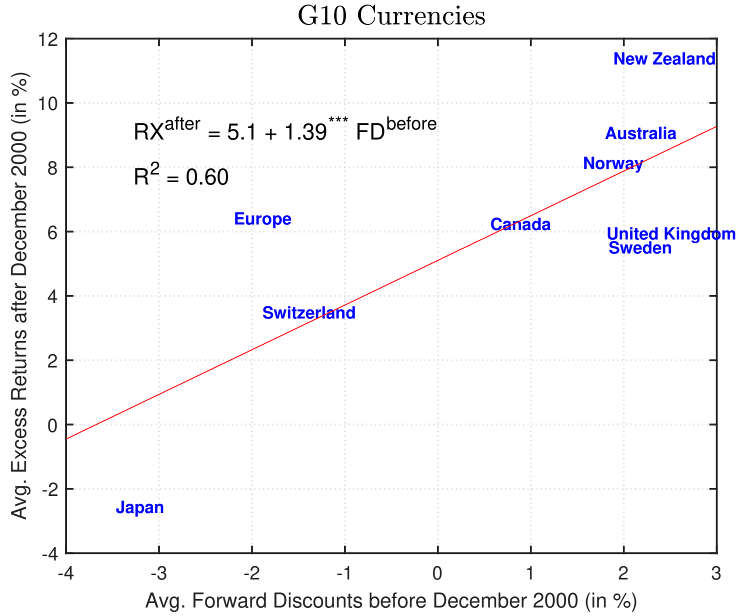
			Panel A: **All Countries**				
	P_L	P_2	P_3	P_4	P_H	*Avg*	*H/L*
Mean	−1.76	0.29	−0.50	0.09	2.44	0.11	4.21
	[−0.91]	[0.15]	[−0.27]	[0.05]	[1.00]	[0.06]	[2.67]
Sdev	7.70	8.71	9.01	9.06	11.19	8.24	9.06
SR	−0.23	0.03	−0.06	0.01	0.22	0.01	0.46
Skew	0.08	−0.35	−0.17	−0.22	−0.73	−0.25	−0.79
Kurt	3.06	3.87	4.07	4.55	6.38	4.27	6.12
pre-β	−0.42	−0.02	0.15	0.37	0.92		
post-β	−0.43	−0.02	0.15	0.37	0.92		
pre-f. f-s	−0.95	−0.54	−0.07	0.69	2.12		
post-f. f-s	−0.96	−0.55	−0.05	0.72	2.14		
Tech Diffusion	8.48	8.89	9.11	9.88	11.13		
			Panel B: **G10 Currencies**				
	P_L	P_2	P_3	P_4	P_H	*Avg*	*H/L*
Mean	−1.08	−1.81	−1.13	−0.56	2.33	−0.45	3.41
	[−0.66]	[−1.02]	[−0.54]	[−0.25]	[0.91]	[−0.24]	[1.95]
Sdev	7.86	8.79	9.50	9.43	11.35	7.90	10.29
SR	−0.14	−0.21	−0.12	−0.06	0.21	−0.06	0.33
Skew	0.29	−0.21	−0.21	−0.22	−0.44	−0.13	−0.76
Kurt	3.94	3.88	3.53	5.03	5.56	4.14	5.79
pre-β	−0.37	0.14	0.31	0.48	0.81		
post-β	−0.38	0.14	0.31	0.48	0.81		
pre-f. f-s	−1.80	−0.64	−0.22	0.69	1.47		
post-f. f-s	−1.82	−0.63	−0.23	0.69	1.48		
Tech Diffusion	8.46	8.26	8.97	9.88	10.43		

Notes: This table presents the summary statistics of portfolios sorted on betas of tech-diffusion-sorted portfolios (AMI). The betas are estimated based on 36-month windows. The first (last) portfolio P_L (P_H) comprises the basket of all currencies with the lowest (highest) technology diffusion betas. H/L is a long-short strategy that buys P_H and sells P_L, and Avg is the average return across portfolios each time. The table presents the annualized mean, standard deviation (in percentage points), and Sharpe ratios. We also report skewness and kurtosis. Figures in square brackets represent Newey and West (1987) t-statistics corrected for heteroskedasticity and autocorrelation (HAC) with 12 lags. "pre-f. f-s" ("post-f. f-s") is the pre-formation (post-formation) forward discount. "pre-β" ("post-β") is the pre-formation (post-formation) beta.

results for G10 currencies.

First, we find that the average forward discounts increase monotonically from the low-beta currencies to the high-beta ones. A larger sensitivity to global shocks makes currencies in the last portfolio a risky investment from the U.S. investors' perspective, causing a higher risk premium. Therefore, sorting based on the forward discounts (fd) and sorting based on risk exposure (betas) are closely related. The result also implies that the forward discount may contain information about the riskiness of an individual currency. Moreover, the excess returns also tend to increase

Figure 6: Forward Discounts and Excess Returns before and after December 2000



Notes: The figure shows the unconditionally-sorted currency returns based on the first-half sample forward discount. The x-axis is the average forward discount of each currency between January 1993 and December 2000. The y-axis is the average excess return of each currency between January 2001 and December 2007. We cut the data after the Global Financial Crisis. The data are collected from Datastream *via* Barclays and Reuters.

from the first to the last portfolio, and for the full sample, the spread of high-minus-low (H/L) is even larger than the one created by the sorts on tech diffusion (4.21 vs. 2.82). In addition, the beta-sorting strategy produces a spread of Sharpe ratios comparable to our baseline tech-diffusion sorts.

The last three lines in each panel show the pre- and post-formation betas and the average tech-diffusion levels in each portfolio. The pre-and post-formation betas vary monotonically from the first to the last, indicating that the rebalancing of portfolios based on this sorting strategy is infrequent. The average tech-diffusion level also increases with the betas. It suggests that the currencies that covary more with our AMI factor come from the countries with a high tech-diffusion index.

3.6 Unconditional Currency Returns

Since the international transmission of R&D is a slow-moving factor for the currency risk premium, for most countries, our tech-diffusion measures are quite stable over time.[27] It is important to consider what proportion of the unconditional carry trade returns rather than conditional ones can be explained by the tech-diffusion factor (AMI). We construct the unconditional carry trade portfolios using the mean forward discount in the first several years of our sample between 1993 and 2001, following Lustig et al. (2011a). We drop the data after the Global Financial Crisis since it is well known that currency excess returns have largely been influenced by a series of monetary easing policies after that date.[28] Figure 6 plots the average excess returns from 2001 to 2007 (referred to as RX^{after}) against the mean forward discounts in the first-half sample (referred to as FD^{before}) for the G10 currencies. We find that the average forward discount in the first-half sample is a strong positive predictor for the countries' future currency excess returns. The fitted line explains 60% of its cross-sectional variation.

Panel A of table 6 shows the summary statistics of unconditional carry trade portfolios sorted on the mean forward discount in the first-half sample. For comparison, panel B shows the statistics of conditional carry trade portfolios in the second-half sample (between 2001 and 2007). First, we find that sorts on average forward discounts produce monotonic currency excess returns in the second-half sample with a spread of 9.66% (6.74%) in the full (G10) sample, even though the spread is smaller than the one produced by conditional sorts (10.22% and 10.13%). The premium on the unconditional carry trade strategy is statistically significant, with a Sharpe ratio that is even larger than one (1.45 and 1.05). Moreover, the forward discount implied by unconditional sorts is virtually monotonic from the first to the last, indicating that interest rates are persistent for individual currencies.

Table B.7 in appendix B shows the unconditionally and conditionally sorted portfolios based on the half-sample average tech diffusion or the previous-year tech diffusion. The unconditional tech-diffusion strategy is labeled $UAMI$. We notice that the currency premium implied by the $UAMI$

[27] See figure C.9 in appendix C for countries' relative rankings based on the tech-diffusion measure.

[28] **?** provide similar evidence and claim that the lower risk premium underlying the traditional carry trade strategy in the post-2008 episode is due to the sharp decline in expected global growth and global inflation.

strategy is also smaller than the premium from the conditional one (AMI), but the difference between these two is relatively small compared with the carry trade strategies. The reason is that our tech diffusion is a long-run factor, and countries' relative rankings in the sample barely alternate across the sample periods.

Table 6: Summary Statistics: Carry Trade Portfolios Sorted on Half Samples: HML^{FX} and $UHML^{FX}$

	Panel A: Sorted on Average Forward Discounts											
	P_L	P_2	P_3	P_4	P_H	$UHML^{FX}$	P_L	P_2	P_3	P_4	P_H	$UHML^{FX}$
	All Countries						**G10 Currencies**					
	Log Excess Returns: rx^j						Log Excess Returns: rx^j					
Mean	1.94	5.45	6.84	8.82	11.60	9.66	1.94	4.88	8.15	7.31	8.68	6.74
	[0.60]	[1.96]	[1.92]	[2.79]	[3.34]	[4.89]	[0.60]	[0.89]	[2.27]	[2.03]	[2.84]	[3.07]
Sdev	7.27	6.90	9.53	8.20	9.84	6.66	7.27	6.63	9.97	9.16	7.90	6.42
SR	0.27	0.79	0.72	1.0	1.18	1.45	0.27	0.74	0.82	0.80	1.10	1.05
	Forward Discount: $f^j - s^j$						Forward Discount: $f^j - s^j$					
Mean	-1.62	-0.56	0.52	2.43	2.76	4.38	-1.62	-0.85	1.10	1.13	2.48	4.09
	[-4.65]	[-3.17]	[1.68]	[3.05]	[10.09]	[22.59]	[-4.65]	[-3.17]	[1.68]	[3.05]	[10.09]	[22.59]
	Panel B: Sorted on Previous-Month Forward Discounts											
	P_L	P_2	P_3	P_4	P_H	HML^{FX}	P_L	P_2	P_3	P_4	P_H	HML^{FX}
	Log Excess Returns: rx^j						Log Excess Returns: rx^j					
Mean	1.85	5.23	8.60	8.38	12.06	10.22	0.49	3.90	8.87	7.46	10.62	10.13
	[0.61]	[1.52]	[3.06]	[2.94]	[3.51]	[4.39]	[0.15]	[1.20]	[2.64]	[2.81]	[2.84]	[3.71]
Sdev	7.67	8.39	7.10	7.18	9.04	6.58	7.66	8.20	8.79	7.07	9.61	8.39
SR	0.24	0.62	1.21	1.17	1.33	1.55	0.06	0.48	1.01	1.06	1.10	1.21
	Forward Discount: $f^j - s^j$						Forward Discount: $f^j - s^j$					
Mean	-2.02	-0.18	0.54	1.61	4.39	6.42	-2.50	-0.30	0.21	1.16	3.23	5.73
	[-5.87]	[-0.49]	[1.44]	[4.16]	[9.41]	[33.96]	[-7.66]	[-0.82]	[0.53]	[3.58]	[11.75]	[52.90]

Notes: This table shows the summary statistics of quintile currency portfolios sorted on the average forward discount between January 1993 and December 2000 (panel A) or the previous-month forward discount (panel B). All the moments are calculated based on portfolio returns in the sample between January 2001 to December 2007. The first (last) portfolio P_L (P_H) comprises 20% of all currencies with the lowest (highest) value of the forward discount or tech-diffusion index. HML^{FX} and $UHML^{FX}$ are the conditional and unconditional long-short strategies that buy P_H and sell P_L of the portfolios. Moreover, the table presents the annualized mean, standard deviation (in percentage points), and Sharpe ratios. Figures in square brackets represent Newey and West (1987) t-statistics corrected for heteroskedasticity and autocorrelation (HAC) using the optimal number of lags.

Asset-Pricing Implications. Table 7 shows asset-pricing tests if we use the five unconditional carry trade portfolios as test assets. Compared with the baseline exercise in table 4, we find that the AMI factor has stronger predicting power for the unconditional currency risk premium. This is not surprising given that our tech-diffusion measure captures the unconditional properties of countries. [29] Specifically, the factor price estimates (λ_{AMI}) are always positive and highly significant in both samples. Regarding the goodness of fit of the model, the cross-sectional R^2 equals 77% for the full sample and 99% for the G10 currencies, higher than the baseline case when using conditional carry trade portfolios as test assets. The χ^2 tests indicate that we cannot reject the null hypothesis that cross-sectional pricing errors are equal to zero, implying a strong pricing ability. Panel B shows the results of the first-pass regression. The coefficients on the DOL factor are always close to one because it serves as a level factor. The coefficients on the AMI factor increase almost monotonically from the first to the last portfolio, indicating their heterogeneous exposure to a common source of risk.

Next, we consider by how much proportion the return of AMI strategy can be used to explain the unconditional excess return of the carry trade ($UHML^{FX}$). To do that, we run the following time-series regression:

$$fac_t = \alpha + \beta AMI_t + \gamma fac_{t-1} + \epsilon_t, \tag{11}$$

where fac is the currency excess return of either HML^{FX} or $UHML^{FX}$. To make a comparison with the unconditional carry trade strategy, we also construct a conditional carry trade strategy for the second-half sample between 2001 and 2007 and label it $HML^{FX}(2)$. Table 8 shows the results, where we omit the estimate of γ. We find that in all specifications, the return on AMI is highly correlated with the carry trade and that the beta coefficients are all significant. However, the unexplained currency excess returns (alphas) are more significant for conditional strategies than unconditional carry trade strategies. This latter result implies that the conditional carry trade may contain more information than the unconditional carry and that the sorts on tech diffusion measure unveil the heterogeneous exposure to a common risk factor that is unconditional in its nature.

[29] Table B.8 in appendix B shows asset-pricing test results when we use DOL and $UAMI$ as risk factors. The risk factor sorted on the mean tech diffusion still has explanatory power for the cross-sectional returns of the unconditional carry trades.

Table 7: Asset-Pricing Tests for Unconditional Carry Portfolios: *DOL* and *AMI* Factors

Panel A: Factor Prices

	λ_{DOL}	λ_{AMI}	χ^2	R^2	$RMSE$	λ_{DOL}	λ_{AMI}	χ^2	R^2	$RMSE$
			All Countries					**G10 Currencies**		
GMM_1	5.80	11.66	2.36	0.77	1.20	5.65	7.70	1.51	0.99	0.81
	(3.14)	(3.31)	{0.50}			(3.28)	(2.49)	{0.68}		
GMM_2	5.74	12.49	2.31			6.24	7.94	1.51		
	(3.10)	(3.12)	{0.51}			(3.18)	(2.47)	{0.68}		
FMB	5.81	11.27	4.74			5.65	7.58	2.22		
(NW)	(2.66)	(3.40)	{0.32}			(2.73)	(2.58)	{0.70}		
(Sh)	(2.67)	(3.69)				(2.73)	(2.65)			

Panel B: Factor Betas

	α	β_{DOL}	β_{AMI}	R^2		α	β_{DOL}	β_{AMI}	R^2
P_L	0.13	0.95	−0.35	0.84	P_L	0.13	0.97	−0.51	0.87
	(0.08)	(0.05)	(0.06)			(0.08)	(0.05)	(0.06)	
P_2	0.42	0.94	−0.09	0.89	P_2	0.38	0.86	−0.12	0.83
	(0.07)	(0.03)	(0.04)			(0.09)	(0.04)	(0.05)	
P_3	0.53	1.22	0.12	0.82	P_3	0.64	1.06	0.24	0.65
	(0.10)	(0.06)	(0.11)			(0.17)	(0.08)	(0.14)	
P_4	0.70	0.96	0.23	0.71	P_4	0.57	1.15	0.19	0.88
	(0.12)	(0.06)	(0.13)			(0.10)	(0.06)	(0.08)	
P_H	0.92	1.25	0.21	0.83	P_H	0.69	0.88	0.26	0.74
	(0.11)	(0.07)	(0.11)			(0.12)	(0.05)	(0.08)	

Notes: This table reports the asset-pricing results for the two-factor model that comprises the *DOL* and *AMI* risk factors. *AMI* stands for the return on a high-minus-low currency strategy sorted on the previous-year tech-diffusion measure. We only use the sample between January 2001 and December 2007 for estimation. We use as test assets the five carry trade portfolios sorted on the first-half-sample mean forward discount between January 1993 and December 2000.

Table 8: Explanatory Regressions for Currency Risk Factors

	All Countries			**G10 Countries**		
	HML^{FX}	$HML^{FX}(2)$	$UHML^{FX}$	HML^{FX}	$HML^{FX}(2)$	$UHML^{FX}$
α	0.53***	0.70***	0.52**	0.48***	0.47**	0.32
	(0.13)	(0.20)	(0.19)	(0.14)	(0.22)	(0.20)
β	0.69***	0.74***	0.52***	0.88***	1.13***	0.68***
	(0.09)	(0.14)	(0.14)	(0.08)	(0.15)	(0.13)
Adj. R^2	0.34	0.40	0.18	0.53	0.53	0.35
No. of Obs	167	71	71	167	71	71

Notes: This table presents the results of the following time-series regression: $fac_t = \alpha + \beta AMI_t + \gamma fac_{t-1} + \epsilon_t$. The estimate of γ is omitted from the table. fac_t represents the conditional and unconditional carry trade returns of either HML^{FX}, $HML^{FX}(2)$ or $UHML^{FX}$. Specifically, HML^{FX} is the conditional carry trade return between January 1993 and December 2007 based on the previous-month forward spread. $UHML^{FX}$ is the unconditional carry trade return sorted on the mean forward spread between January 1993 and December 2000. The currency excess returns are calculated based on the second-half sample from January 2001 to December 2007. For comparison, $HML^{FX}(2)$ is the conditional carry trade return only on the second-half sample only. Standard errors in parentheses are based on Newey and West (1987). *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

4 Additional Results

This section first provides an alternative sorting strategy based on international technology spillover that complements our baseline tech-diffusion measure. Then we compare our tech-diffusion risk factor with the related risk factors (import ratio and trade centrality) in the literature.

4.1 Double-Sorting Strategy

Our tech-diffusion index captures the trade concentration of an R&D recipient country, weighted by the innovation efforts (R&D expenditures) of all its trade partner countries. This concept represents the direction and intensity of the R&D content in the manufacturing trade flows. However, the tech-diffusion measure is silent about the R&D expenditure of the home (tech-adoption) country. In this section, following the methods of Della Corte et al. (2016) and Cespa et al. (2022), we consider a 2×3 double-sorting strategy based on the importers' R&D ratios and trade concentrations (not weighted by R&D), respectively.[30]

First, we modify the baseline measure (defined in section 2) and calculate an importing country's trade concentration (TC) as follows,

$$TC_{imp} = \left[\sum_{exp=1}^{N} (IM_{imp,exp})^2 \right]^{1/2} , \text{ for } imp = 1, 2, \ldots, N \ , \tag{12}$$

where the intensive margin of trade is not adjusted by R&D from the country's trade partners; that is, $IM_{imp,exp} = \widehat{TI}^{GDP}_{imp,exp} / \widehat{EM}_{imp,exp}$[31]. We construct the double-sorting portfolios as follows: at the end of each period t, we first group currencies into two baskets using the countries' R&D ratios in year y-1; then we reorder currencies within each basket using the above-defined trade concentration (TC) value in year y-1. Figure C.16 in appendix C provides an illustration for the double-sorting strategy. In the end, we allocate currencies into six portfolios so that P_{13} corresponds to low-R&D

[30] Della Corte et al. (2016) consider a 2×3 double-sorting strategy based on countries' net foreign asset (nfa) positions and the fraction of liabilities denominated in domestic currencies (ldc). Similarly, Cespa et al. (2022) consider a 3×3 double-sorting strategy based on the previous-24-hour average currency returns and FX transaction volumes.

[31] $\widehat{TI}^{GDP}_{imp,exp}$ and $\widehat{EM}_{imp,exp}$ are, respectively, the normalized intensive and extensive margins of trade; that is, $\widehat{TI}^{GDP}_{imp,exp} = TI^{GDP}_{imp,exp} / \sum_{exp=1}^{N} TI^{GDP}_{imp,exp}$ and $\widehat{EM}_{imp,exp} = EM_{imp,exp} / \sum_{exp=1}^{N} EM_{imp,exp}$.

Table 9: Double-Sorting Currency Portfolios

Panel A: **All Countries**							
	P_{21}	P_{22}	P_{23}	P_{11}	P_{12}	P_{13}	$AMI^{2\times3}$
Mean	-0.41	-1.23	2.17	0.43	1.03	2.72	3.13
	[-0.22]	[-0.69]	[1.31]	[0.23]	[0.53]	[1.24]	[2.41]
Sdev	8.57	8.99	8.43	8.48	8.79	10.25	6.91
SR	-0.05	-0.14	0.26	0.05	0.12	0.27	0.45
Skewness	-0.23	-0.00	-0.18	-0.46	-0.41	-0.50	-0.19
FD	-0.65	-1.04	0.33	0.54	0.95	2.34	2.99
	[-2.55]	[-4.87]	[1.18]	[1.90]	[3.82]	[9.34]	[11.26]
RIR	0.17	-0.25	0.86	0.63	0.87	1.74	1.56
R&D (%)	2.31	2.43	2.94	1.26	1.29	1.26	
Trade Concentration	6.65	8.72	11.11	6.21	7.79	13.39	
Panel B: **G10 Currencies**							
	P_{21}	P_{22}	P_{23}	P_{11}	P_{12}	P_{13}	$AMI^{2\times3}$
Mean	-1.68	-2.28	-0.47	-0.39	0.17	1.53	3.21
	[-0.79]	[-1.15]	[-0.25]	[-0.21]	[0.08]	[0.72]	[2.15]
Sdev	9.59	10.02	9.93	8.60	9.62	9.75	7.84
SR	-0.18	-0.23	-0.05	-0.04	0.02	0.16	0.41
Skewness	-0.18	0.11	-0.17	-0.50	-0.65	-0.49	-0.39
FD	-1.18	-1.32	-1.54	0.56	0.88	1.59	2.77
	[-4.13]	[-6.32]	[-4.70]	[3.15]	[4.38]	[8.55]	[15.52]
RIR	-0.20	0.17	0.05	0.70	0.99	1.76	1.96
R&D (%)	2.28	2.47	2.25	1.53	1.25	1.21	
Trade Concentration	6.16	8.56	9.69	7.69	9.18	17.72	

Notes: This table presents the summary statistics of the double-sorting (2×3) currency portfolios. In the first sort, we divide the sample into two categories based on R&D-to-GDP ratios, while in the second sort, we further divide each portfolio into three based on the trade concentration measure. The portfolio P_{13} (P_{21}) contains the currencies simultaneously having a low (high) value of R&D and a high value of trade concentration. We denote $AMI^{2\times3}$ as the long-short strategy that buys P_{13} and sells P_{21}. The table presents the annualized mean, standard deviation (in percentage points), and Sharpe ratios. We also report forward discounts and real interest rate differentials for each portfolio. Figures in square brackets represent Newey and West (1987) t-statistics corrected for heteroskedasticity and autocorrelation (HAC) using the optimal number of lags. The data are collected from Datastream *via* Barclays and Reuters and contain monthly series from January 1993 to December 2019.

countries that receive a high trade concentration and P_{21} represents high-R&D countries with a low trade concentration. The double-sorting (denoted by $AMI^{2\times3}$) refers to a strategy that goes long in P_{13} and short in P_{21}. We should note that the procedure does not guarantee monotonicity in our sorting variables. For example, the trade concentration in P_{23} doesn't need to be higher than that in P_{11}. But the corner portfolios contain the intended set of countries.

Table 9 shows portfolio statistics based on the double-sorting strategy. We notice that the R&D ratio is higher in $P_{1\cdot}$ than in $P_{2\cdot}$, which is natural by construction. Also, the trade concentration is monotonic in the second sorting direction: $[P_{11}, P_{12}, P_{13}]$ and $[P_{21}, P_{22}, P_{23}]$. Most importantly, we find that the double-sorting strategy generates a positive and significant spread of currency returns in the corner portfolios: $AMI^{2\times3} = P_{13} - P_{21}$. Compared with the return on tech diffusion (in table 3), the double-sorting strategy generates similar excess returns, Sharpe ratios, and t-statistics. The spread of forward discounts is slightly higher than the baseline. However, we also notice that the returns are not monotone in the degree of trade concentration, especially in the high-R&D group. Figure C.17 in appendix C contrasts the cumulative returns of the double-sorting and tech-diffusion strategies. The correlation of returns is 0.76 in the full sample and 0.61 using the G10 currencies.

We should be aware that even though the double-sorting strategy generates a similar return as our baseline model, the strategies contain different information. The double-sorting strategy considers the importers' R&D while the tech-diffusion strategy considers the technology spillover due to the exporters' R&D effort. In the double-sorting strategy, we select the countries with a low innovation effort but that are actively importing manufactured goods, and it turns out that the currencies of these countries have higher returns than their counterparts, the countries conducting innovations but that are more reluctant to import manufactured goods from other countries. In that sense, our original tech-diffusion measure is a direct measure representing the R&D components of trade flows, while the double-sorting strategy gives an indirect measure, ranking countries based on their innovation efforts and trade connections.[32]

Table B.9 in appendix B shows asset-pricing tests using the return of the double sort as a risk factor ($AMI^{2\times3}$). The estimate of the factor price is always positive and significant, and the estimation is more precise than that based on our baseline tech-diffusion measure (smaller standard errors). Also, in the first pass of FMB regression, we find that the double-sort factor generates a larger spread of betas than the tech-diffusion factor ($\beta_H - \beta_L = 0.68$ and 0.82 vs. $\beta_H - \beta_L = 0.54$ and 0.62), indicating that the double-sorting strategy can better account for the heterogeneous risk exposure of the tail portfolios.

[32]Figures C.10-C.13 in appendix C compare the portfolio turnover rates of the two sorting strategies. The identity of currencies in the two extreme portfolios mostly coincide, but there are exceptions. For example, the euro is almost always considered a funding currency under tech-diffusion sorts, but sometimes it is missed under double-sorts. The opposite is true for the Swedish krona.

4.2 A Comparison of Currency Risk Factors: Import Ratio (IMX) and Trade Centrality (PMC)

In this section, we compare the performance of our factor with two trade-based factors that have demonstrated success in explaining the cross-section of the currency risk premium.

The first is the IMX factor of Ready et al. (2017) that is constructed based on the countries' import ratios.[33] Specifically, IMX is a long-short strategy that buys currencies of commodity exporters (i.e., high import ratio) and goes short in the currencies of commodity importers (i.e., low import ratio). The relative advantage in producing basic goods endows the commodity producer with an ability to insure itself and makes the final goods producer's currency a safe haven. Second, we consider the PMC factor of Richmond (2019), which is the return on a portfolio that buys the currencies of central countries and sells the currencies of peripheral economics. Since central countries are more exposed to the global consumption risk, their currencies generate lower returns than those of the periphery economies. To facilitate the comparison, we consider the reverse strategy of PMC (denoted by $PMC^{(-)}$). Moreover, in this section, we use Ready et al. (2017)'s sample of 22 countries – a common subset of our sample and Richmond (2019)'s sample.

Table 10 shows the summary statistics of all three trade-based currency risk factors, together with the carry trade returns.[34] We notice that both the AMI and IMX strategies offer significant excess returns. The excess returns delivered by AMI and IMX account for 77% and 92% of the carry trade strategy, respectively. Moreover, the AMI factor generates the largest Sharpe ratio among all the risk factors, even larger than that of the traditional carry trade. Furthermore, the skewness of the AMI factor is weaker than those of all the other factors. The AMI factor exhibits the smallest disaster risk: the maximum drawdown in the history equals 8%, smaller than the 12% under IMX and HML^{FX}.

Figure C.19 in appendix C provides a visual illustration for the relationship between the three

[33] The import ratio is defined as follows: Net Imports of Complex Goods + Net Exports of Basic Goods / Manufacturing Output.

[34] Table B.10 in appendix B shows the correlations between alternative risk factors. We find that all factors exhibit moderate correlations with each other. The AMI factor has a relatively tighter correlation with IMX (0.62) than with $PMC^{(-)}$ (0.53). Among the three trade-based factors, IMX has the strongest correlation with the carry trade return at 0.64.

Table 10: Summary Statistics of Alternative Currency Risk Factors

	HML^{FX}	AMI	IMX	$PMC^{(-)}$	$AMI^{2\times3}$
Mean	4.40	3.38	4.06	2.25	3.24
	[2.24]	[2.84]	[2.10]	[1.58]	[2.30]
SD	9.66	6.56	9.10	6.83	7.95
Sharpe Ratio	0.45	0.51	0.45	0.33	0.41
Skewness	-0.78	0.07	-1.04	-0.03	-0.15
Kurtosis	5.58	3.36	9.35	4.32	3.51
Max. Drawdown	-0.12	-0.08	-0.12	-0.08	-0.10

Notes: This table presents the statistics of alternative currency risk factors. $PMC^{(-)}$ is the currency risk factor sorted based on prior-year trade network centrality (as in Richmond, 2019) and goes long in central countries and short in peripheral countries (the reverse of PMC). IMX is the currency factor sorted based on the previous-year import ratio (as in Ready et al., 2017) and goes long in high-import-ratio currencies and short in low-import-ratio currencies. HML^{FX} is the carry factor sorted based on previous-month forward spreads. Means and standard deviations are reported in percentage points.

factors by comparing countries' relative rankings. We find that the rankings based on tech diffusion and the import ratio are positively correlated, indicating that countries adopting technologies abroad are also the ones that export commodity goods. In the same sense, adopter countries are usually periphery economies in the global trade network, although the connection between tech diffusion and centrality is looser than the connection between tech diffusion and the import ratio. There are many exceptions: Korea is a high-tech-diffusion country, but it produces final complex goods and imports basic goods. Portugal has a low-tech-diffusion index, but it is peripheral to the trade network.

The results in table 10 and figure C.19 show that the three trade-based factors are not perfectly correlated. However, we still need to examine more directly whether our tech-diffusion factor produces additional information over IMX and PMC in explaining the cross-section of currency returns. To do that, we first regress the AMI factor on IMX or PMC and extract the estimated residuals (denoted by $AMI^{\perp IMX}$ and $AMI^{\perp PMC}$). Then we include the orthogonalized risk factors in a two-factor asset-pricing model (together with DOL) to consider their predictabilities.

Table 11 displays the asset-pricing tests for the orthogonalized risk factors.[35] The left panel

[35] For comparison, table B.11 in appendix B shows the baseline two-factor asset-pricing tests using Ready et al. (2017)'s sample of 22 countries.

Table 11: Asset-Pricing for Orthogonalized Risk Factors: IMX and PMC

Panel A: Factor Prices

	λ_{DOL}	$\lambda_{AMI^{\perp IMX}}$	χ^2	R^2	$RMSE$	λ_{DOL}	$\lambda_{AMI^{\perp PMC}}$	χ^2	R^2	$RMSE$
	Import Ratio (IMX)					**Trade Centrality (PMC)**				
GMM_1	1.17	8.93	6.81	0.37	1.38	−0.09	10.39	1.86	0.75	0.58
	(2.12)	(4.14)	{0.08}			(1.90)	(4.78)	{0.60}		
GMM_2	2.32	12.84	5.83			−0.18	13.89	1.66		
	(1.97	(4.71)	{0.12}			(1.87)	(5.56)	{0.65}		
FMB	1.18	8.13	9.64			−0.08	10.29	2.60		
(NW)	(1.79)	(3.41)	{0.05}			(1.60)	(3.74)	{0.63}		
(Sh)	(1.79)	(3.69)				(1.60)	(4.16)			

Panel B: Factor Betas

	α	β_{DOL}	$\beta_{AMI^{\perp IMX}}$	R^2		α	β_{DOL}	$\beta_{AMI^{\perp PMC}}$	R^2
P_L	−0.11	0.78	0.01	0.52	P_L	−0.18	0.80	−0.26	0.57
	(0.11)	(0.08)	(0.16)			(0.10)	(0.07)	(0.10)	
P_2	−0.07	0.99	−0.15	0.86	P_2	−0.16	0.96	−0.09	0.83
	(0.05)	(0.04)	(0.05)			(0.05)	(0.03)	(0.05)	
P_3	0.14	0.97	−0.15	0.85	P_3	0.01	0.96	−0.03	0.81
	(0.05)	(0.03)	(0.06)			(0.06)	(0.03)	(0.06)	
P_4	0.10	1.03	−0.02	0.81	P_4	0.00	1.03	0.07	0.81
	(0.08)	(0.05)	(0.07)			(0.07)	(0.04)	(0.07)	
P_H	0.35	1.23	0.27	0.80	P_H	0.23	1.24	0.24	0.80
	(0.09)	(0.05)	(0.10)			(0.08)	(0.04)	(0.08)	

Notes: This table reports the asset-pricing results for a two-factor model that comprises the DOL and $AMI^{\perp IMX}$ or $AMI^{\perp PMC}$ risk factors. $AMI^{\perp IMX}$ represents the part of the tech-diffusion factor orthogonalized to Ready et al. (2017)'s commodity trade factor, while $AMI^{\perp PMC}$ represents the part of the tech-diffusion factor orthogonalized to Richmond (2019)'s trade centrality factor. We use as test assets five currency portfolios sorted based on past forward discounts (i.e., carry trade portfolios). We rebalance the portfolios on a monthly basis. The data cover from January 1993 to December 2012 for the IMX factor and from January 1993 to December 2016 for the PMC factor. Panel A reports GMM_1, GMM_2, and the Fama and MacBeth (1973) estimates of the factor prices (λ). Panel B reports the OLS estimates of the contemporaneous time-series regression with HAC standard errors in parentheses.

shows the results of orthogonalization to IMX, while the right panel shows the PMC. In both cases, the orthogonalized risk factor still has strong predicting power for the cross-sectional variation in currency returns. The estimated factor prices are statistically significant. The pricing errors are insignificant for the orthogonalization on PMC and marginally significant for the IMX. Overall, the two-factor models can still explain 37% and 75% of the cross-sectional variation in carry trade returns, respectively. The values of R^2 are not much lower than that of the baseline asset-pricing test (0.37 and 0.75 vs. 0.84 in table B.11). Panel B shows the time-series regression coefficients in the first pass of FMB. The five carry portfolios have heterogeneous exposure to our residual factors, although the betas are not monotonic for the factor orthogonalized to IMX.

5 A Simple Model of Tech Diffusion

This section builds an asymmetric two-country environment to consider how the heterogeneous exposure to global shocks generates currency risk premia. The process of innovation and adoption follows Comin and Gertler (2006) and Comin et al. (2009).[36] The economy lasts for two periods: $t = 1, 2$. In the first period, agents receive endowments and decide on the R&D investments, including innovation and adoption efforts. Production only happens in the second period after patents are invented or adopted. The home country (referred to as country-H) only has the innovation technology, while the foreign country (referred to as country-F) can either innovate patents or adopt patents from the home country.[37] Innovation and adoption are modeled as a love-of-variety process as in Romer (1990). In country-F, the size of the innovation (adoption) sector is μ $(1-\mu)$.

A domestically invented patent only requires domestic intermediate goods as production inputs, while the adopted patent requires intermediate goods imported from abroad. As a result, in country-F, the relative benefits of adopting and innovating depend on the cost of the intermediate goods and the real exchange rate. In the following, we will use this model to show that endogenous innovation and adoption create the technology transmission between the two countries and produce exchange rate dynamics close to the data.

We assume that the productivities are persistent and follow a bivariate log-normal distribution:

$$\begin{bmatrix} \log(z^h) \\ \log(z^f) \end{bmatrix} \sim \mathcal{N}\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma^2 & \rho\sigma^2 \\ \rho\sigma^2 & \sigma^2 \end{bmatrix} \right). \tag{13}$$

The shocks are observed at the beginning of the first period before innovators and adopters make their investment decisions. We assume the first-period endowments are $y_1^h = z^h$, $y_1^f = z^f$.[38]

[36] Our model shares many similar features with that of Comin et al. (2014), who study technology transmission from developed (N) to developing (S) economies.

[37] In the online appendix, we build another version of the model where both countries have an adoption sector. We can prove that the same mechanism works if the adoption sector in the home country is smaller than the one in the foreign country.

[38] The exogenous process is symmetric between the two countries. That allows us to focus on the endogenous asymmetry in our model that arises from the one-direction technology diffusion.

The Second-Period Problem. In period 2, the final goods are produced with intermediate goods based on the following production functions:

$$y_2^h = z^h \left[\sum_{i=1}^{N_2^h} (x_{2,i}^h)^{\xi} \right], \tag{14}$$

$$y_2^f = z^f \left[\mu^{1-\xi} \sum_{i=1}^{N_2^f} (x_{2,i}^f)^{\xi} + (1-\mu)^{1-\xi} \sum_{j=1}^{N_{h,2}^f} (x_{h,2,j}^f)^{\xi} \right]. \tag{15}$$

where N_2^h and N_2^f denote the number of domestically invented patents. $N_{h,2}^f$ represents the number of patents adopted by country-F after they are designed in country-H. We assume that in both countries, producing one intermediate good (x_2^h, x_2^f) costs one unit of final consumption. For the adopted patents in country-F, using one imported intermediate good ($x_{h,2}^f$) costs $1/e_2$ units of final consumption. e_2 denotes the real exchange rate level in the second period, which represents the units of country-H's consumption goods per country-F's consumption.[39]

In addition, final goods can be transported across the border but incur a shipping cost. For X_2 units of consumption goods exported by country-F, country-H only receives $X_2\left(1 - \frac{\kappa}{2}X_2\right)$ in the units of its own consumption. There is a continuum of final goods importers. Their zero-profit condition implies that,

$$e_2 = 1 - \frac{\kappa}{2} X_2. \tag{16}$$

There is no shipping cost in the first period, indicating that the real exchange rate always equals one: $e_1 = 1$. The resource constraints in the home and foreign countries are

$$y_2^h = c_2^h + N_2^h x_2^{h*} - X_2 \left(1 - \frac{\kappa}{2} X_2\right) + N_{h,2}^f x_{h,2}^{f*}, \tag{17}$$

$$y_2^f = c_2^f + N_2^f x_2^{f*} + X_2. \tag{18}$$

In period 2, firms' profit maximization implies the optimal level of intermediate inputs as follows,

$$x_2^{h*} = \xi^{\frac{1}{1-\xi}} z^{h,\frac{1}{1-\xi}}, \qquad x_2^{f*} = \mu \xi^{\frac{1}{1-\xi}} z^{f,\frac{1}{1-\xi}}, \qquad x_{h,2}^{f*} = (1-\mu) \xi^{\frac{1}{1-\xi}} z^{f,\frac{1}{1-\xi}} e_2^{\frac{1}{1-\xi}}. \tag{19}$$

[39] An increase in e_2 indicates a real depreciation in the home country.

The production functions can be simplified to the following,

$$y_2^h = \xi^{\frac{\xi}{1-\xi}} z^{h, \frac{1}{1-\xi}} N_2^h, \qquad y_2^f = \xi^{\frac{\xi}{1-\xi}} z^{f, \frac{1}{1-\xi}} \left[\mu N_2^f + (1-\mu) N_{h,2}^f e_2^{\frac{\xi}{1-\xi}} \right]. \tag{20}$$

The real depreciation in the home country reduces the cost of adoption in the foreign economy and stimulates foreign country's production.

The First-Period Problem. In period 1, agents receive endowment incomes, make consumption decisions, and choose innovation and adoption. Innovation and adoption are associated with the following cost functions:[40]

$$F_h(N_2^h) = \chi (N_2^h)^{1+\eta}, \qquad F_f(N_2^f) = \bar{\chi} (N_2^f)^{1+\eta}, \qquad F_{h,f}(N_{h,2}^f, N_2^h) = \chi^a \exp^{\{b_1 N_{h,2}^f - b_2 N_2^h\}}. \tag{21}$$

We notice that the marginal cost of innovation is increasing in the number of patents, indicating a congestion effect in the R&D market. The adoption technology has two features: First, the congestion effect also appears. The cost of adoption is exponentially increasing in the adopted number of varieties with an elasticity b_1. Second, the home country's innovation effort generates a positive externality and reduces the foreign country's adoption cost: an international diffusion effect. As more patents are designed in country-H, the world's technological frontier rises, and as a result, country-F also finds it cheaper to adopt. This assumption is consistent with the tech adoption literature as in Comin and Hobijn (2010) and Comin et al. (2014).[41]

We suppose at the beginning of the first period, there is a social planner maximizing global welfare,

$$U = \sum_{t=1}^{2} \sum_{i=h,f} u(c_t^i). \tag{22}$$

[40]In Comin and Gertler (2006) and Santacreu (2015)'s models, the probability of success for an adopter is an increasing function of its adopting effort. In our model, we use the cost function of adoption in order to derive analytical solutions.

[41]Based on this functional form, country-H's innovation has a second-order effect: the marginal cost of adoption decreases in the number of innovated patents in country-H; that is, $\partial F_{h,f}(N_{h,2}^f, N_2^h)/\partial N_2^h < 0$ and $\partial^2 F_{h,f}(N_{h,2}^f, N_2^h)/[\partial N_2^h \partial N_{h,2}^f] < 0$.

subject to the resource constraint:

$$c_1^h + c_1^f + F_h(N_2^h) + F_f(N_2^f) + F_{h,f}(N_{h,2}^f, N_2^h) = z^h + z^f. \tag{23}$$

We assume the financial market is complete. The social planner can optimally allocate resources and coordinate the development of technologies in the two countries.[42] In particular, her problem is to choose the allocations $\{c_1^h,\ c_1^f,\ N_2^h,\ N_2^f,\ N_{h,2}^f,\ c_2^h,\ c_2^f,\ X_2,\ x_2^h,\ x_2^f,\ x_{h,2}^f\}$ that maximize the global welfare (22) subject to equations (14), (15), (19), (16), (17), (18), and (23).

Taking derivatives yields the first-order conditions for the social planner as follows:

$$(1+\eta)\chi(N_2^h)^\eta = \mathcal{M}_2^h \tilde{\xi} z^{h,\frac{1}{1-\xi}} + \mathcal{M}_2^f \frac{b_2}{b_1}(1-\mu)\tilde{\xi} z^{f,\frac{1}{1-\xi}} e_2^{\frac{\xi}{1-\xi}}, \tag{24}$$

$$(1+\eta)\bar{\chi}(N_2^f)^\eta = \mathcal{M}_2^f \mu \tilde{\xi} z^{f,\frac{1}{1-\xi}}, \tag{25}$$

$$\chi^a b_1 \exp^{\{b_1 N_{h,2}^f - b_2 N_2^h\}} = \mathcal{M}_2^f (1-\mu)\tilde{\xi} z^{f,\frac{1}{1-\xi}} e_2^{\frac{\xi}{1-\xi}}, \tag{26}$$

where $\tilde{\xi} = \xi^{\frac{\xi}{1-\xi}} - \xi^{\frac{1}{1-\xi}}$. In addition, the pricing kernels and risk-sharing condition are given by

$$\mathcal{M}_2^h = \frac{\lambda_2^h}{\lambda_1} = \frac{u'(c_2^h)}{u'(c_1)}, \qquad \mathcal{M}_2^f = \frac{\lambda_2^f}{\lambda_1} = \frac{u'(c_2^f)}{u'(c_1)}, \qquad e_2 = \frac{\lambda_2^f}{\lambda_2^h}. \tag{27}$$

Ultimately, the solution of the model is characterized by equations (19), (20), (16), (17), (18), (23), (24), (25), (26), and (27).

The timeline proceeds as follows: In the first period, after the shocks of $[z^h, z^f]'$ are realized, the social planner chooses the optimal levels of innovation and adoption. Then in the second period, intermediate goods are exported from the home country to the foreign country. Next, final goods are produced using either the innovated or adopted patents. Lastly, the consumption goods are traded with a shipping cost.

One can notice that the model features two potentially complementary mechanisms, both of

[42] The online appendix shows a decentralized version of the model, which is equivalent to the social planner's problem. Conceptually, the competitive equilibrium should be different from the social planner's solution because there exists a congestion effect from innovation activities. Since this is a standard feature of endogenous growth models and our paper focuses on the model's asset-pricing implications, we only solve the social planner's problem in the main text.

which contribute to the heterogeneous shock exposure. First, the home innovation effort creates a positive externality on the effective productivity in the foreign country. Second, our trade structure is asymmetric. The foreign country imports home intermediate goods, but the home country does not import foreign intermediate goods. After solving the model, we can show that the second endogenous mechanism is quantitatively more important for our conclusions.

5.1 Analytical Solutions

To study the carry trade strategy and currency excess returns, we define the interest rates in the home and foreign countries as $r^h = \log(R^h) = -\log \mathbb{E}[\mathcal{M}_2^h]$, $r^f = \log(R^f) = -\log \mathbb{E}[\mathcal{M}_2^f]$. The excess return (in log) of shorting the home-currency deposits and buying foreign-currency deposits is written as $rx_2 = r^f - r^d + \Delta \log e_2$. For comparison, we also compute the excess return in level $RX_2 = \frac{R^f}{R^h}\frac{e_2}{e_1}$.

Next, we provide analytical solutions based on the log-linearization of the model around its deterministic steady state where productivity shocks degenerate. Then, we show the numerical result of the generalized model. Denote $\hat{x}$ as the log-deviation of variable x around its deterministic steady state. We first make the following assumption.

Assumption 1. *Households have a quasi-linear preference:* $U = c_1^h + c_2^{h,1-\sigma}/(1-\sigma) + c_1^f + c_2^{f,1-\sigma}/(1-\sigma)$*. Moreover, innovating and adopting firms are risk neutral.*

The assumption of preference and the risk neutrality simplify the expression of the interest rate and allows us to characterize the properties of the solution.[43] In addition, since country-H's innovating activity has an externality effect on country-F, our numerical solution implies that the social planner's optimal plan is to run a current account deficit for country-H in period 1 to accelerate its innovation. In the second period, the depreciated exchange rate increases its intermediate goods export, which benefits country-F's adoption. The following assumption excludes this intertemporal financial flow channel and simplifies the solution.

Assumption 2. *Countries have balanced trade in each period; that is,* $X_2 e_2 = N_{h,2}^f x_{h,2}^{f*}$.

[43] The online appendix builds a model to incorporate CRRA utility and risk-averse firms. We find that all the mechanisms in this section apply to this generalization.

Based on the above assumptions, the optimality conditions of innovation and adoption in equations (24)-(26) can be reexpressed as follows:

$$\hat{N}_2^h = A_1 \hat{z}^h + A_2 \hat{z}^f + A_3 \hat{e}_2, \tag{28}$$
$$\hat{N}_2^f = \frac{1}{\eta}\frac{1}{1-\xi}\hat{z}^f, \tag{29}$$
$$\hat{N}_{h,2}^f = \frac{b_2}{b_1}A_1\hat{z}^h + \left(\frac{b_2}{b_1}A_2 + \frac{1}{b_1}\frac{1}{1-\xi}\right)\hat{z}^f + \left(\frac{b_2}{b_1}A_3 + \frac{1}{b_1}\frac{\xi}{1-\xi}\right)\hat{e}_2. \tag{30}$$

where coefficients are

$$A_1 = \frac{\frac{1}{1-\xi}\frac{1}{\eta}}{1+\frac{b_2}{b_1}(1-\mu)}, \qquad A_2 = \frac{\frac{1}{1-\xi}\frac{1}{\eta}\frac{b_2}{b_1}(1-\mu)}{1+\frac{b_2}{b_1}(1-\mu)}, \qquad A_3 = \frac{\frac{\xi}{1-\xi}\frac{1}{\eta}\frac{b_2}{b_1}(1-\mu)}{1+\frac{b_2}{b_1}(1-\mu)}. \tag{31}$$

Taking equations (28)-(30) into the linearized version of resource constraints (17) and (18) and using the risk-sharing condition (27), we have the following expressions of exchange rate and consumption in the second period:

$$\hat{e}_2 = \frac{\overbrace{\left[A_1\left(1-(1-\mu)\frac{b_2}{b_1}\right)+\frac{1}{1-\xi}\right]}^{E}\hat{z}^h + \overbrace{\left[A_2\left(1-(1-\mu)\frac{b_2}{b_1}\right)-\frac{1}{1-\xi}\left(1+\frac{\mu}{\eta}+\frac{1-\mu}{b_1}\right)\right]}^{F}\hat{z}^f}{\underbrace{\frac{1}{\sigma}-A_3\left(1-(1-\mu)\frac{b_2}{b_1}\right)+(1-\mu)\frac{\xi}{1-\xi}\left(1+\frac{1}{b_1}\right)}_{D}}, \tag{32}$$

$$\hat{c}_2^h = \underbrace{\left(A_1+\frac{1}{1-\xi}+A_3\frac{E}{D}\right)}_{\tilde{C}_1^D}\hat{z}^h + \underbrace{\left(A_2+A_3\frac{F}{D}\right)}_{\tilde{C}_2^D}\hat{z}^f, \tag{33}$$

$$\begin{aligned}\hat{c}_2^f = &\overbrace{\left[(1-\mu)\frac{b_2}{b_1}A_1+(1-\mu)\left(\frac{\xi}{1-\xi}\left(1+\frac{1}{b_1}\right)+\frac{b_2}{b_1}A_3\right)\frac{E}{D}\right]}^{\tilde{C}_1^F}\hat{z}^h \\ &+\underbrace{\left[\frac{1}{1-\xi}\left(1+\frac{\mu}{\eta}+\frac{1-\mu}{b_1}\right)+(1-\mu)\frac{b_2}{b_1}A_2+(1-\mu)\left(\frac{\xi}{1-\xi}\left(1+\frac{1}{b_1}\right)+\frac{b_2}{b_1}A_3\right)\frac{F}{D}\right]}_{\tilde{C}_2^F}\hat{z}^f.\end{aligned} \tag{34}$$

The following lemma describes how the exchange rate responds to productivity shocks.

Lemma 1. *Under the conditions (i)* $\frac{1}{\sigma}+(1-\mu)\frac{\xi}{1-\xi}\left(1+\frac{1}{b_1}\right) > A_3\left(1-(1-\mu)\frac{b_2}{b_1}\right)$ *and (ii)* $\frac{1}{\eta}\left(1-\frac{b_2}{b_1}\right) > \frac{1}{b_1}$*, we argue that*

a. the real exchange rate in country-H depreciates if there is an increase in global productivity; that is, $\frac{\partial \hat{e}_2}{\partial \hat{z}} > 0$*, where* $\hat{z}^h = \hat{z}^f = \hat{z}$*;*

b. *the real exchange rate in country-H depreciates if the difference in productivity is widened between H and F; that is,* $\frac{\partial \hat{e}_2}{\partial \hat{\epsilon}} > 0$*, where* $\hat{z}^h = -\hat{z}^f = \hat{\epsilon}$*.*

Proof. See appendix A.1. □

The lemma indicates that an asymmetry shows up even when there is a common shock to global productivity. The home currency depreciates in good times and appreciates in bad times, which is a natural hedge for investors in the FX market. The first condition is a regularity condition. The second condition holds only when the adoption elasticity b_1 is big enough or the diffusion effect b_2 is small enough. The former assumption is consistent with the view in the literature that cross-border technology adoption is a slow-moving process (e.g., Comin et al., 2009; Gavazzoni and Santacreu, 2020). A small tech-diffusion parameter b_2 is necessary to generate the asymmetric risk exposure between two countries. The following lemma describes how consumption and output depend on shocks.

Lemma 2. *Under the same conditions as in lemma 1, we argue that*

a. *country-H's consumption increases by more than the consumption in country-F when there is a positive shock to global productivity; that is,* $\frac{\partial \hat{c}_2^h}{\partial \hat{z}} > \frac{\partial \hat{c}_2^f}{\partial \hat{z}} > 0$*, where* $\hat{z}^h = \hat{z}^f = \hat{z}$*,*

b. *the global output increases when there is a mean-preserving productivity shock between H and F; that is,* $\frac{\partial \hat{y}_2}{\partial \hat{\epsilon}} = \frac{1}{2}\frac{\partial(\hat{c}_2^h + \hat{c}_2^f)}{\partial \hat{\epsilon}} > 0$ *where* $\hat{z}^h = -\hat{z}^f = \hat{\epsilon}$*.*

Proof. See appendix A.2. □

The first part of lemma 2 implies that the home country is more exposed to global productivity shocks than the foreign country. More importantly, the second part of lemma 2 implies that the "good times" are usually the economic states where country-H's productivity is higher than that of country-F. Or put another way, the global business cycle (i.e., the fluctuation of output $\hat{y}_2$) is led by country-H.

Currency Return and Consumption Comovement. Given the above properties, we have the following proposition to characterize the risk premium for investing in the foreign currency.

Define the log pricing kernel as $m_2^h = \log(\mathcal{M}_2^h)$, $m_2^f = \log(\mathcal{M}_2^f)$. Then, the exchange rate change is given by $\Delta \log(e_2) = m_2^f - m_2^h$.

Proposition 1. *Suppose conditions (i) and (ii) in lemma 1 hold and we assume the following condition (iii) holds:*

$$\frac{1}{1-\xi}\left(1+\frac{\mu}{\eta}+\frac{1-\mu}{b_1}\right) > (1-\mu)\frac{b_2}{b_1}(A_1 - A_2) + (1-\mu)\left[\frac{\xi}{1-\xi}\left(1+\frac{1}{b_1}\right)+\frac{b_2}{b_1}A_3\right]\frac{E-F}{D}.$$

Then the currency risk premium for going long in F and short in H is positive; that is,

$$\mathbb{E}\left[rx_2\right] = r^f - r^h + \mathbb{E}\left[\Delta \log e_2\right] = \frac{1}{2}var(m_2^h) - \frac{1}{2}var(m_2^f) > 0, \tag{35}$$

$$\log(\mathbb{E}\left[RX_2\right]) = -cov(m_2^h, \Delta \log e_2) > 0. \tag{36}$$

Moreover, the carry trade return is procyclical: $cov(\hat{y}_2, rx_2) = cov(\hat{y}_2, \log e_2) > 0$.

Proof. See appendix A.3. □

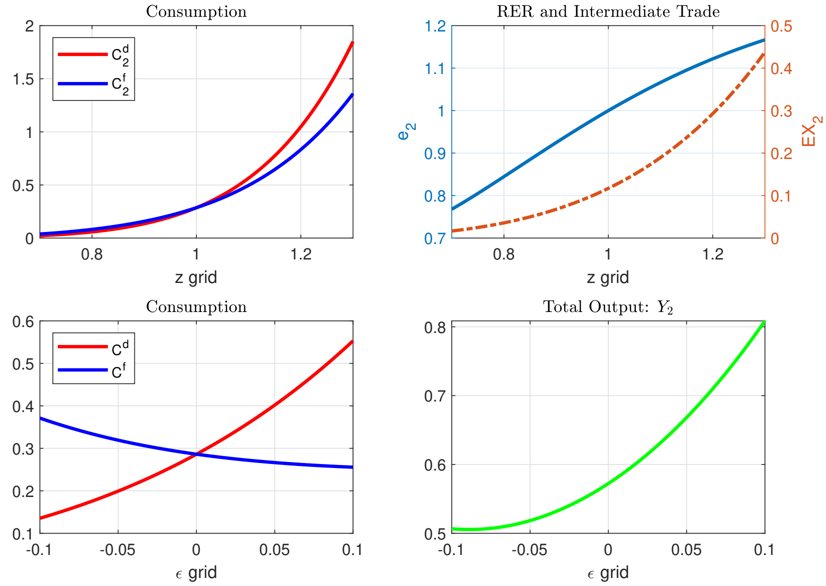
Proposition 1 indicates that the higher shock exposure of the home country makes its currency less risky than the foreign currency. As a result, investors charge a risk premium on country-F's currency to compensate for their loss due to the depreciation in the downturns. The carry trade returns also positively comove with global output. We have this currency risk structure because the two countries have heterogeneous exposure to global shocks (as in lemma 2). Condition (iii) holds when the size of the adoption sector $(1-\mu)$ is not too large. Next, the following proposition describes the correlation between SDFs and the cyclicality of intermediate export from the home country.

Proposition 2. *Suppose conditions (i)-(iii) hold. Then the correlation of SDFs is higher than the correlation of productivity shocks; that is,*

$$corr(m_2^h, m_2^f) = corr(\hat{c}_2^h, \hat{c}_2^f) > corr(z^h, z^f). \tag{37}$$

Moreover, the intermediate export from the home country is procyclical, $corr(\hat{y}_2, \widehat{EX}_2) > 0$, *if and*

Figure 7: Consumption Risk Sharing in a Two-Country Diffusion Model



Note: This picture shows the functions of consumption, the real exchange rate, and world production in the simplified model. The parameter values are as follows: $\sigma = 0.5$, $\mu = 0.5$, $\xi = 0.45$, $\eta = 0.35$, $b_1 = 2$, and $b_2 = 0.3$. In the upper panel, we consider a common productivity shock in the two countries; that is, $\hat{z}^h = \hat{z}^f = \hat{z}$. In the lower panel, we consider a mean-preserving shock; that is, $\hat{z}^h = -\hat{z}^f = \hat{\epsilon}$.

only if the following condition (iv) holds:

$$\frac{b_2}{b_1}A_1 + \left(\frac{b_2}{b_1}A_3 + \frac{1}{b_1}\frac{\xi}{1-\xi} + \frac{1}{1-\xi}\right)\frac{E-F}{D} > \frac{b_2}{b_1}A_2 + \frac{1}{1-\xi}\left(\frac{1}{b_1}+1\right).$$

Proof. See appendix A.4. □

5.2 Numerical Illustration

Figure 7 provides a numerical illustration of the model by showing the schedules of consumption, output, the real exchange rate, and intermediate trade. First, we find that the slope of domestic consumption is larger than that of foreign consumption, indicating that country-H is more sensitive to global shocks than country-F (in both dimensions of z and ϵ). Second, country-H leads the business cycle. The good states are associated with a larger output expansion in the home country. Third, country-H's currency depreciates in good times and appreciates in bad times, providing a financial hedge for FX market investors. In an economic expansion, the depreciated home currency stimulates the intermediate imports of its trade partner.

Figure 8 shows the predicted moments of the model for different levels of shock correlation ρ_{fd}.[44] The upper left panel shows the currency risk premium (in levels and logs) and the exchange rate volatility. A larger shock correlation (ρ_{fd}) reduces the benefits of risk-sharing between the two countries and thus decreases the risk premium. In the upper right panel, we find that due to the endogenous tech-diffusion process, the cross-country correlation of SDFs is always larger than the correlation of shocks, which confirms proposition 2.

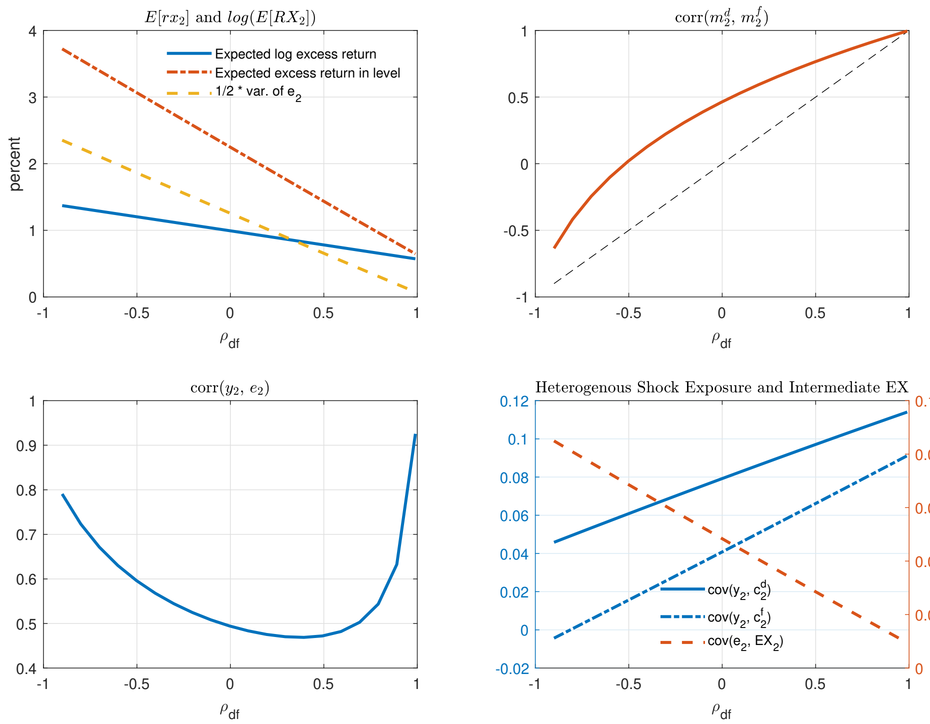
In the bottom left panel, we find that the exchange rate is always procyclical, but its correlation with output is not monotone in ρ_{fd}. Specifically, a mildly positive shock correlation (ρ_{fd} at around 0.5) generates the weakest correlation between the exchange rate and output. The bottom right panel shows that home consumption is always more exposed to the global business cycle than foreign consumption and that the difference in the two correlations (solid and dashed blue lines) gets narrower as productivity shocks more strongly comove. Furthermore, a larger ρ_{fd} weakens the correlation between the exchange rate and intermediate export from the home country.

6 Conclusions

This paper examines the role of technology diffusion in the foreign exchange market. In particular, we link the currency risk premium and carry trade profitability with tech diffusion. Carry trade is a FX market investment strategy that goes long in the high-interest-rate currencies and short in the low-interest-rate currencies. First, we define tech diffusion as the concentration of R&D in the imports of intermediate goods. Then our currency risk factor (tech-diffusion factor) is a zero-cost strategy that involves a long position in the high-tech-diffusion portfolio (i.e., the adopters' currencies) and a short position in low-tech-diffusion portfolio (i.e., the innovators' currencies). Using a two-factor asset-pricing model, we find that the tech-diffusion factor is priced in the cross-section of the carry trade returns and that the predicting power holds under alternative specifications. Intuitively, carry traders require a risk premium for holding the adopters' currencies as compensation for the elevated exchange rate risk since the high-tech-diffusion currencies depreciate in bad times

[44] In figure C.20 of appendix C, we show the model simulation results by varying the size of the adoption sector $(1-\mu)$.

Figure 8: Simulated Moments at Different Levels of Shock Correlation (ρ_{df})



Note: This picture shows model-implied moments at different levels of shock correlation ρ_{df}. The baseline parameter values are the same as in figure 7. The numerical expectations are evaluated using the Gauss-Hermite quadrature.

and appreciate in good times. We rationalize our findings in an asymmetric two-country environment. The model can account for countries' heterogeneous risk exposure to global productivity shocks and suggests a persistent currency risk premium.

The pricing ability of our model is further confirmed by constructing the beta-sorted portfolios, where the individual currency more exposed to the tech-diffusion factor generated higher returns than the currency less exposed to the factor. We also show that the tech-diffusion measure contains important information for both conditional and unconditional currency returns. Moreover, our results hold after controlling for the transaction costs of the carry trade. Finally, we contrast our tech-diffusion measure with alternative trade-based risk factors in the literature. We find that the orthogonalized risk factors still have predicting ability for the cross-section of currency excess returns.

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Appendix

A Proof of Propositions

A.1 Proof of Lemma 1

Proof. **The first half:** In order to prove that $\frac{\partial \hat{e}_2}{\partial \hat{z}} > 0$, we only need to show that $E + F > 0$ and $D > 0$. Given the expression of E and F in equation (32), we have the following

$$E + F = (A_1 + A_2)\left(1 - (1-\mu)\frac{b_2}{b_1}\right) - \frac{1}{1-\xi}\left(\frac{\mu}{\eta} + \frac{1-\mu}{b_1}\right). \tag{A.1}$$

Based on the expressions of A_1 and A_2 in equation (28), we have $A_1 + A_2 = \frac{1}{\eta}\frac{1}{1-\xi}$. Then, after simplification, $E + F > 0$ is equivalent to condition (ii) in Lemma 1. Moreover, given the expression of D in equation (32), we can see that $D > 0$ is equivalent to condition (i) in Lemma 1. Consequently, $\hat{e}_2$ is always an increasing function of $\hat{z}$ under the specified conditions.

The second half: In order to prove that $\frac{\partial \hat{e}_2}{\partial \hat{\epsilon}} > 0$, we only need to show that $E - F > 0$. Given the expressions of E and F, we have the following

$$\begin{aligned} E - F &= (A_1 - A_2)\left(1 - (1-\mu)\frac{b_2}{b1}\right) + \frac{1}{1-\xi}\left(2 + \frac{\mu}{\eta} + \frac{1-\mu}{b_1}\right), \\ &= \frac{1}{1-\xi}\frac{1}{\eta}\frac{\left[1 - \frac{b_2}{b_1}(1-\mu)\right]^2}{1 + \frac{b_2}{b_1}(1-\mu)} + \frac{1}{1-\xi}\left(2 + \frac{\mu}{\eta} + \frac{1-\mu}{b_1}\right) > 0 \end{aligned} \tag{A.2}$$

As a result, $\hat{e}_2$ is always an increasing function of $\hat{\epsilon}$.

□

A.2 Proof of Lemma 2

Proof. **The first half:** First, we prove that home consumption is more sensitive to a global productivity shock than the foreign country: $\frac{\partial \hat{c}_2^h}{\partial \hat{z}} > \frac{\partial \hat{c}_2^f}{\partial \hat{z}} > 0$. Using the expressions in equation

(33)-(34), that only requires us to prove the following

$$\tilde{C}_1^D + \tilde{C}_2^D > \tilde{C}_1^F + \tilde{C}_2^F > 0, \tag{A.3}$$

$$\Longleftrightarrow$$

$$(A_1 + A_2) + A_3 \frac{E+F}{D} > (A_1 + A_2)(1-\mu)\frac{b_2}{b_1} + \tag{A.4}$$
$$\frac{1}{1-\xi}\left(\frac{\mu}{\eta} + \frac{1-\mu}{b_1}\right) + (1-\mu)\left[\frac{\xi}{1-\xi}\left(1+\frac{1}{b_1}\right) + \frac{b_2}{b_1}A_3\right]\frac{E+F}{D},$$

$$\Longleftrightarrow$$

$$(A_1 + A_2)\left(1 - (1-\mu)\frac{b_2}{b_1}\right) + \tag{A.5}$$
$$\frac{E+F}{D}\left[\left(1-(1-\mu)\frac{b_2}{b_1}\right)A_3 - (1-\mu)\frac{\xi}{1-\xi}\left(1+\frac{1}{b_1}\right)\right] > \frac{1}{1-\xi}\left(\frac{\mu}{\eta} + \frac{1-\mu}{b_1}\right)$$

Given that $E + F = (A_1 + A_2)\left(1 - (1-\mu)\frac{b_2}{b_1}\right) - \frac{1}{1-\xi}\left(\frac{\mu}{\eta} + \frac{1-\mu}{b_1}\right) > 0$ and $D > 0$ under conditions (i)-(ii), the equation (A.5) is simplified to the following

$$D + A_3\left(1 - (1-\mu)\frac{b_2}{b_1}\right) - (1-\mu)\frac{\xi}{1-\xi}\left(1 + \frac{1}{b_1}\right) > 0$$

Using the expression of D in equation (32), the above equation only requires $\frac{1}{\sigma} > 0$, which always holds.

Besides, $\tilde{C}_1^F + \tilde{C}_2^F$ equals to the right-hand side of equation (A.4) that is always positive. Therefore, we have proved that $\hat{c}_2^h$ is more sensitive than $\hat{c}_2^f$ to a common shock on the global productivity $\hat{z}$.

The second half: Next, we prove that when the home country productivity dominates the foreign country by a larger amount (an increase in $\hat{\epsilon}$), the global output also increases: $\frac{\partial \hat{y}_2}{\partial \hat{\epsilon}} = \frac{1}{2}\frac{\partial(\hat{c}_2^h + \hat{c}_2^f)}{\partial \hat{\epsilon}} > 0$. That is, we need to prove the following relationship

$$\tilde{C}_1^D - \tilde{C}_1^D + \tilde{C}_1^F - \tilde{C}_2^F > 0. \tag{A.6}$$

Using the expressions in equation (33)-(34), that requires the following

$$
\begin{aligned}
&(A_1 - A_2)\left(1 + (1-\mu)\frac{b_2}{b_1}\right) - \frac{1}{1-\xi}\left(\frac{\mu}{\eta} + \frac{1-\mu}{b_1}\right) + \\
&\frac{E-F}{D}\left[A_3\left(1 + (1-\mu)\frac{b_2}{b_1}\right) + (1-\mu)\frac{\xi}{1-\xi}\left(1 + \frac{1}{b_1}\right)\right] > 0.
\end{aligned} \tag{A.7}
$$

Based on (A.1), the first two terms add up to $E + F > 0$. Given that we know $E - F > 0$ and $D > 0$, the inequality (A.7) always holds. Therefore, we have proved that the global output increases when there is positive mean-preserving shock on productivity of the two countries.

□

A.3 Proof of Proposition 1

Proof. Because we assumed households are risk neutral in period 1, we have the following expression of interest rate difference and currency risk premium,

$$
\begin{aligned}
r^f - r^h &= \left[-\log(\mathbb{E}\mathcal{M}_2^f)\right] - \left[-\log(\mathbb{E}\mathcal{M}_2^h)\right] \\
&= \left[-\mathbb{E}m_2^f - \frac{1}{2}\text{var}(m_2^f)\right] - \left[-\mathbb{E}m_2^h - \frac{1}{2}\text{var}(m_2^h)\right].
\end{aligned} \tag{A.8}
$$

$$
\Delta\log(e_2) = \hat{e}_2 = m_2^f - m_2^h, \tag{A.9}
$$

$$
\begin{aligned}
\mathbb{E}[rx_2] &= r^f - r^h + \mathbb{E}[\hat{e}_2] \\
&= \frac{1}{2}\text{var}(m_2^h) - \frac{1}{2}\text{var}(m_2^f) = \frac{1}{2}\sigma^2\left(\text{var}(\hat{c}_2^h) - \text{var}(\hat{c}_2^f)\right).
\end{aligned} \tag{A.10}
$$

The currency risk premium (in level) is given by

$$
\begin{aligned}
\log(\mathbb{E}[RX_2]) &= \mathbb{E}[rx_2] + \frac{1}{2}\text{var}(\hat{e}_2), \\
&= \frac{1}{2}\sigma^2\left(\text{var}(\hat{c}_2^h) - \text{var}(\hat{c}_2^f)\right) + \frac{1}{2}\text{var}(\hat{e}_2), \\
&= -\text{cov}(m_2^h, \hat{e}_2).
\end{aligned} \tag{A.11}
$$

We assume $\hat{z} = \frac{\hat{z}^h + \hat{z}^f}{2}$ and $\hat{\epsilon} = \frac{\hat{z}^h - \hat{z}^f}{2}$, then these two components are independent of each other: $\text{cov}(\hat{z}, \hat{\epsilon}) = 0$. Based on solutions of the model in equations (33)-(34), we have

$$\hat{c}_2^h = (\tilde{C}_1^D + \tilde{C}_2^D)\hat{z} + (\tilde{C}_1^D - \tilde{C}_2^D)\hat{\epsilon}, \tag{A.12}$$

$$\hat{c}_2^f = (\tilde{C}_2^F + \tilde{C}_1^F)\hat{z} - (\tilde{C}_2^F - \tilde{C}_1^F)\hat{\epsilon} \tag{A.13}$$

The condition (iii) in proposition 1 guarantees that $\tilde{C}_2^F - \tilde{C}_1^F > 0$. That is to say, a positive $\hat{\epsilon}$ shock reduces the output in country-F. Then, based on the proof of Lemma 2, we have

$$|\tilde{C}_1^D + \tilde{C}_2^D| > |\tilde{C}_2^F + \tilde{C}_1^F|, \tag{A.14}$$

$$|\tilde{C}_1^D - \tilde{C}_2^D| > |\tilde{C}_2^F - \tilde{C}_1^F|, \tag{A.15}$$

which leads to the following

$$\begin{aligned} \text{var}(\hat{c}_2^h) &= (\tilde{C}_1^D + \tilde{C}_2^D)^2\sigma^{z,2} + (\tilde{C}_2^F + \tilde{C}_1^F)^2\sigma^{\epsilon,2} \\ &> (\tilde{C}_1^D - \tilde{C}_2^D)^2\sigma^{z,2} + (\tilde{C}_2^F - \tilde{C}_1^F)^2\sigma^{\epsilon,2} = \text{var}(\hat{c}_2^f). \end{aligned} \tag{A.16}$$

The larger risk exposure of the home country results in the lowered risk premium in the currency market: $\mathbb{E}[rx_2] > 0$. Moreover, the currency risk premium in level is

$$\log(\mathbb{E}[RX_2]) = \mathbb{E}[rx_2] + \frac{1}{2}\text{var}(\hat{e}_2) > 0. \tag{A.17}$$

The second-period global output and exchange rate are given by,

$$\hat{y}_2 = \frac{1}{2}\left(\tilde{C}_1^D + \tilde{C}_2^D + \tilde{C}_2^F + \tilde{C}_1^F\right)\hat{z} + \frac{1}{2}\left(\tilde{C}_1^D + \tilde{C}_1^F - \tilde{C}_2^D - \tilde{C}_2^F\right)\hat{\epsilon}, \tag{A.18}$$

$$\hat{e}_2 = \frac{E+F}{D}\hat{z} + \frac{E-F}{D}\epsilon. \tag{A.19}$$

Since we focus on the unconditional excess returns, then

$$\begin{aligned}
&cov(\hat{y}_2, rx_2) = cov(\hat{y}_2, \hat{e}_2) \\
&= \frac{1}{2}\left(\tilde{C}_1^D + \tilde{C}_2^D + \tilde{C}_2^F + \tilde{C}_1^F\right)\frac{E+F}{D}\sigma^{z,2} + \frac{1}{2}\left(\tilde{C}_1^D + \tilde{C}_1^F - \tilde{C}_2^D - \tilde{C}_2^F\right)\frac{E-F}{D}\sigma^{\epsilon,2}.
\end{aligned}$$

Due to the conditions (i)-(iii) and the implied relationshipts $E+F>0$, $E-F>0$, and $D>0$, we have $cov(\hat{y}_2, rx_2) > 0$; that is the excess return for going long in currency F and short in currency H is procyclical.

□

A.4 Proof of Proposition 2

Proof. **The first half:** By the definition of $\hat{z}$ and $\hat{\epsilon}$ in the proof of proposition 1, we have the following,

$$\mathrm{cov}(\hat{z}^h, \hat{z}^f) = \mathrm{cov}(\hat{z}+\hat{\epsilon}, \hat{z}-\hat{\epsilon}) = \sigma^{z,2} - \sigma^{\epsilon,2} = \sigma^{z,2}(1-\bar{\rho}) \tag{A.20}$$

$$\mathrm{var}(\hat{z}+\hat{\epsilon}) = \mathrm{var}(\hat{z}-\hat{\epsilon}) = \sigma^{z,2}(1+\bar{\rho}) \tag{A.21}$$

where we define $\bar{\rho} = \frac{\sigma^{\epsilon,2}}{\sigma^{z,2}}$. Then, we have

$$\mathrm{corr}(\hat{z}^h, \hat{z}^f) = \frac{1-\bar{\rho}}{1+\bar{\rho}}, \qquad \text{where} \quad \bar{\rho} \in [0, \infty). \tag{A.22}$$

Based on the equations (33) and (34), we have

$$\begin{aligned}
\mathrm{corr}(\hat{c}_2^h, \hat{c}_2^f) &= \frac{\left(\tilde{C}_1^D + \tilde{C}_2^D\right)\left(\tilde{C}_2^F + \tilde{C}_1^F\right)\sigma^{z,2} - \left(\tilde{C}_1^D - \tilde{C}_2^D\right)\left(\tilde{C}_2^F - \tilde{C}_1^F\right)\sigma^{\epsilon,2}}{\left[\left(\tilde{C}_1^D + \tilde{C}_2^D\right)^2\sigma^{z,2} + \left(\tilde{C}_1^D - \tilde{C}_2^D\right)^2\sigma^{\epsilon,2}\right]^{\frac{1}{2}}\left[\left(\tilde{C}_2^F + \tilde{C}_1^F\right)^2\sigma^{z,2} + \left(\tilde{C}_2^F - \tilde{C}_1^F\right)^2\right]^{\frac{1}{2}}} \\
&= \frac{1 - \frac{(\tilde{C}_1^D - \tilde{C}_2^D)(\tilde{C}_2^F - \tilde{C}_1^F)}{(\tilde{C}_1^D + \tilde{C}_2^D)(\tilde{C}_2^F + \tilde{C}_1^F)}\bar{\rho}}{\left[1 + \left(\frac{\tilde{C}_1^D - \tilde{C}_2^D}{\tilde{C}_1^D + \tilde{C}_2^D}\right)^2\bar{\rho}\right]^{\frac{1}{2}}\left[1 + \left(\frac{\tilde{C}_2^F - \tilde{C}_1^F}{\tilde{C}_2^F + \tilde{C}_1^F}\right)^2\bar{\rho}\right]^{\frac{1}{2}}}.
\end{aligned} \tag{A.23}$$

Under conditions (i)-(iii), we know that $0 < \left(\frac{\tilde{C}_1^D - \tilde{C}_2^D}{\tilde{C}_1^D + \tilde{C}_2^D}\right) < 1$ and $0 < \left(\frac{\tilde{C}_2^F - \tilde{C}_1^F}{\tilde{C}_2^F + \tilde{C}_1^F}\right) < 1$. Since the function $f(a,b) = \frac{1-\bar{\rho}ab}{(1+\bar{\rho}a^2)^{\frac{1}{2}}(1+\bar{\rho}b^2)^{\frac{1}{2}}}$ is decreasing in $a, b \in (0,1]$ for every positive $\bar{\rho}$, we know that,

$$f\left(\frac{\tilde{C}_1^D - \tilde{C}_2^D}{\tilde{C}_1^D + \tilde{C}_2^D}, \frac{\tilde{C}_2^F - \tilde{C}_1^F}{\tilde{C}_2^F + \tilde{C}_1^F}\right) < f(1,1) \Longrightarrow \text{corr}(\hat{c}_2^h, \hat{c}_2^f) > \text{corr}(\hat{z}^h, \hat{z}^f). \tag{A.24}$$

The second half: The export of intermediate goods is given by $EX_2 = (1-\mu)N_{h,2}^f z^{f\,\frac{1}{1-\xi}} e_2^{\frac{1}{1-\xi}} \xi^{\frac{1}{1-\xi}}$. Taking log-linearization and using equation (26) and (32) yields,

$$\begin{aligned}
\hat{EX}_2 &= \hat{N}_{h,2}^f + \frac{1}{1-\xi}\hat{z}^f + \frac{1}{1-\xi}\hat{e}_2 \\
&= \frac{b_2}{b_1}A_1\hat{z}^h + \left[\frac{b_2}{b_1}A_2 + \frac{1}{1-\xi}\left(\frac{1}{b_1}+1\right)\right]\hat{z}^f + \left(\frac{b_2}{b_1}A_3 + \frac{1}{b_1}\frac{\xi}{1-\xi} + \frac{1}{1-\xi}\right)\hat{e}_2 \\
&= \frac{b_2}{b_1}A_1\hat{z}^h + \left[\frac{b_2}{b_1}A_2 + \frac{1}{1-\xi}\left(\frac{1}{b_1}+1\right)\right]\hat{z}^f + \left(\frac{b_2}{b_1}A_3 + \frac{1}{b_1}\frac{\xi}{1-\xi} + \frac{1}{1-\xi}\right)\left(\frac{E}{D}\hat{z}^h + \frac{F}{D}\hat{z}^f\right)
\end{aligned}$$

When z^h and z^f perfectly comove, the shock on the common productivity $\hat{z}$ ensures that $\text{corr}(\hat{y}_2, \hat{EX}_2) > 0$ (because $E + F > 0$). When z^h and z^f negatively comove, the mean-preserving shock $\hat{\epsilon}$ makes the correlation of output and export $\text{corr}(\hat{y}_2, \hat{EX}_2)$ positive if and only if condition (iv) holds. Overall, the shocks structure is a combination of $\hat{z}$ and $\hat{\epsilon}$. Hence, condition (iv) is a sufficient and necessary condition for $\text{corr}(\hat{y}_2, \hat{EX}_2) > 0$ at all $\rho \in [-1,1]$; or $\text{corr}(\hat{y}_2, \hat{EX}_2) > 0$ at all $\bar{\rho} \in [0, \infty)$.

□

B Additional Tables

Table B.1: Cross-Sectional Regressions for Productivity Growth Beta: β_i^z

	All Countries				G10 Countries			
Tech Diffusion	-0.29***	-0.23***	-0.32***	-0.32***	-0.97***	-0.94***	-0.56***	-0.95***
	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.05)	(0.04)	(0.06)
GDP Share		0.82***				0.15***		
		(0.06)				(0.04)		
R&D Ratio			13.07***				23.84***	
			(1.96)				(2.01)	
Trade-to-GDP				0.22***				0.51***
				(0.02)				(0.03)
R^2	0.05	0.06	0.14	0.10	0.37	0.38	0.53	0.51
No. of Obs.	8,184	8,184	8,184	8,184	3,036	3,036	3,036	3,036

Notes: The table shows the cross-sectional Fama and MacBeth (1973) regressions of productivity growth betas on tech-diffusion index (in logs) and other control variables. The estimate of the constant is omitted from the table. Productivity growth beta is calculated as the correlation between a country's labor productivity growth and the world average productivity growth. Figures in parentheses are Newey and West (1987) standard errors corrected for heteroskedasticity and autocorrelation (HAC) using 36 lags. Standard errors are clustered by country. *, **, and *** denote the significance at 10%, 5%, and 1% levels, respectively.

Table B.2: Cross-Sectional Regressions for Consumption Growth Beta: β_i^c

	All Countries				G10 Countries			
Tech Diffusion	-0.23***	-0.17***	-0.23***	-0.24***	-0.15	-0.30**	-0.46***	-0.17
	(0.05)	(0.04)	(0.05)	(0.05)	(0.11)	(0.14)	(0.14)	(0.12)
GDP Share		0.59***				-0.65***		
		(0.09)				(0.11)		
R&D Ratio			-2.45***				-20.41***	
			(0.49)				(2.64)	
Trade-to-GDP				-0.04**				-0.26***
				(0.02)				(0.03)
R^2	0.10	0.14	0.12	0.13	0.14	0.35	0.49	0.23
No. of Obs.	8,184	8,184	8,184	8,184	3,036	3,036	2,796	3,036

Notes: The table shows the cross-sectional Fama and MacBeth (1973) regressions of consumption growth betas on tech-diffusion index (in logs) and other control variables. The estimate of the constant is omitted from the table. Consumption growth beta is calculated as the correlation between a country's consumption growth and the average growth rate for the sample economies. Figures in parentheses are Newey and West (1987) standard errors corrected for heteroskedasticity and autocorrelation (HAC) using 36 lags. Standard errors are clustered by country. *, **, and *** denote the significance at the 10%, 5%, and 1% levels, respectively.

Table B.3: Currency Portfolios with Transaction Costs

Portfolio	P_L	P_2	P_3	P_4	P_H	HML	P_L	P_2	P_3	P_4	P_H	HML
Panel A: Sorted on Technology Diffusion												
	All Countries						**G10 Currencies**					
	Log Excess Returns: rx^j						Log Excess Returns: rx^j					
Mean	-0.81	0.42	-0.22	1.53	1.90	2.72	-1.72	-0.43	1.14	0.41	1.70	3.42
	[-0.45]	[0.23]	[-0.12]	[0.84]	[0.92]	[2.38]	[-0.93]	[-0.25]	[0.50]	[0.24]	[0.81]	[2.46]
	Arithmetic Excess Returns: RX^j						Arithmetic Excess Returns: RX^j					
Mean	-1.27	-0.11	-0.78	1.01	1.30	2.56	-2.23	-0.93	0.56	-0.08	1.10	3.33
Sdev	8.06	8.67	8.92	8.95	9.56	6.35	8.50	8.63	10.92	8.72	9.73	7.92
SR	-0.16	-0.01	-0.09	0.11	0.14	0.40	-0.26	-0.11	0.05	-0.01	0.11	0.42
Panel B: Sorted on Forward Discounts												
	Log Excess Returns: rx^j						Log Excess Returns: rx^j					
Mean	-1.30	-1.13	0.81	-0.15	2.36	3.66	-1.36	-1.66	0.92	-0.57	2.41	3.77
	[-0.73]	[-0.61]	[0.47]	[-0.08]	[1.05]	[2.22]	[-0.79]	[-0.92]	[0.47]	[-0.29]	[-0.03]	[1.89]
	Arithmetic Excess Returns: RX^j						Arithmetic Excess Returns: RX^j					
Mean	-1.85	-1.59	0.36	-0.68	1.66	3.51	-1.89	-2.09	0.51	-1.10	1.74	3.63
Sdev	8.45	8.68	8.24	8.95	10.73	8.07	8.56	8.30	9.16	9.35	10.90	10.00
SR	-0.22	-0.18	0.04	-0.08	0.15	0.44	-0.22	-0.25	0.06	-0.12	0.16	0.36

Notes: This table presents the descriptive statistics of quintile currency portfolios sorted on monthly tech diffusion (panel A) and forward discounts (panel B). The excess returns are in net of transaction costs and expressed in percentage points. The first (last) portfolio P_L (P_H) comprises 20% of all currencies with the lowest (highest) value of tech-diffusion index or forward discount. HML is the a long-short strategy that buys P_H and sells P_L. Moreover, the table presents the annualized mean, standard deviation and Sharpe ratios. Figures in squared brackets represent Newey and West (1987) t-statistics corrected for heteroskedasticity and autocorrelation (HAC) using the optimal number of lags. The data are collected from Datastream *via* Barclays and Reuters and contain monthly series from January 1993 to December 2019.

Table B.4: Portfolios Sorted on Tech-Diffusion Betas: 24-Months Windows

	P_L	$P2$	$P3$	$P4$	P_H	Avg	H/L
All Countries							
Mean	−1.40	0.23	−0.90	−0.36	3.03	0.12	4.43
	[−0.73]	[0.12]	[−0.46]	[−0.18]	[1.38]	[0.06]	[2.90]
Sdev	7.86	8.58	9.50	9.62	10.26	8.19	8.73
SR	−0.18	0.03	−0.10	−0.04	0.30	0.01	0.51
Skew	0.17	−0.07	−0.05	−0.50	−0.46	−0.25	−0.49
Kurt	3.16	3.48	4.42	4.84	6.09	4.25	4.89
pre-β	−0.50	−0.10	0.11	0.35	0.90		
post-β	−0.51	−0.11	0.11	0.35	0.91		
pre-f. f-s	−1.09	−0.25	0.03	0.51	2.01		
post-f. f-s	−1.09	−0.24	0.03	0.49	2.07		
Tech Diffusion	8.52	8.94	9.01	10.29	11.04		
G10 Countries							
	P_L	$P2$	$P3$	$P4$	P_H	Avg	H/L
Mean	−1.29	−1.68	−0.62	0.18	1.75	−0.33	3.04
	[−0.75]	[−0.92]	[−0.29]	[0.08]	[0.73]	[−0.19]	[1.65]
Sdev	7.95	8.67	10.53	9.18	11.09	7.95	10.34
SR	−0.16	−0.19	−0.06	0.02	0.16	−0.04	0.29
Skew	0.35	−0.23	0.04	−0.31	−0.45	−0.08	−0.67
Kurt	4.09	3.96	4.48	4.60	5.79	4.20	5.43
pre-β	−0.40	0.10	0.30	0.45	0.82		
post-β	−0.41	0.10	0.30	0.45	0.83		
pre-f. f-s	−1.81	−0.62	−0.01	0.58	1.46		
post-f. f-s	−1.82	−0.61	−0.03	0.60	1.46		
Tech Diffusion	8.46	8.26	8.97	9.88	10.43		

Notes: This table presents the summary statistics of portfolios sorted on betas with global tech-diffusion portfolios (AMI). The betas are estimated based on 24-months windows. The first (last) portfolio P_L (P_H) comprises the basket of all currencies with the lowest (highest) technology diffusion betas. H/L is a long-short strategy that buys P_H and sells P_L, and Avg is the average across portfolios each time. The table presents the annualized mean, standard deviation (in percentage points), and Sharpe ratios. We also report skewness and kurtosis. Figures in squared brackets represent Newey and West (1987) t-statistics corrected for heteroskedasticity and autocorrelation (HAC) with 12 lags. "pre-f. f-s" ("post-f. f-s") is the pre-formation (post-formation) forward discount "pre-β" ("post-β") is the pre-formation (post-formation) beta. The data contain monthly series from January 1993 to December 2019.

Table B.5: Carry Trade and Tech-Diffusion Portfolios as Test Assets

Panel A: Factor Prices

	λ_{DOL}	λ_{AMI}	χ^2	R^2	$RMSE$	λ_{DOL}	λ_{AMI}	χ^2	R^2	$RMSE$
	All Countries					**G10 Currencies**				
FMB	0.11	4.02	13.58	0.30	1.25	−0.23	4.40	6.92	0.49	1.06
(NW)	(1.55)	(1.37)	{0.14}			(1.52)	(1.75)	{0.65}		
(Sh)	(1.55)	(1.38)				(1.52)	(1.76)			

Panel B: Factor Betas

	α	β_{DOL}	β_{AMI}	R^2		α	β_{DOL}	β_{AMI}	R^2
CT_L	−0.20	0.95	−0.27	0.78	CT_L	−0.19	0.88	−0.40	0.65
	(0.06)	(0.05)	(0.10)			(0.08)	(0.07)	(0.08)	
CT_2	−0.09	0.99	−0.13	0.83	CT_2	−0.14	0.92	−0.13	0.72
	(0.05)	(0.05)	(0.07)			(0.06)	(0.05)	(0.05)	
CT_3	0.08	0.95	−0.05	0.84	CT_3	0.08	0.87	0.08	0.59
	(0.05)	(0.03)	(0.05)			(0.09)	(0.06)	(0.05)	
CT_4	0.01	0.99	0.08	0.83	CT_4	−0.05	1.00	0.17	0.80
	(0.06)	(0.04)	(0.09)			(0.06)	(0.05)	(0.05)	
CT_H	0.21	1.16	0.27	0.85	CT_H	0.19	1.16	0.25	0.82
	(0.07)	(0.05)	(0.11)			(0.07)	(0.04)	(0.07)	
TD_L	−0.11	0.98	−0.44	0.94	TD_L	−0.19	1.01	−0.56	0.92
	(0.03)	(0.02)	(0.03)			(0.04)	(0.02)	(0.03)	
TD_2	−0.00	1.01	−0.11	0.85	TD_2	−0.07	0.93	−0.13	0.69
	(0.07)	(0.04)	(0.07)			(0.08)	(0.07)	(0.05)	
TD_3	−0.06	1.00	−0.03	0.81	TD_3	0.05	1.14	0.17	0.74
	(0.06)	(0.04)	(0.04)			(0.08)	(0.08)	(0.06)	
TD_4	0.09	1.02	0.02	0.85	TD_4	−0.00	0.92	0.09	0.72
	(0.05)	(0.04)	(0.04)			(0.07)	(0.05)	(0.05)	
TD_H	0.11	0.98	0.56	0.96	TD_H	0.10	1.01	0.44	0.94
	(0.03)	(0.02)	(0.03)			(0.04)	(0.02)	(0.03)	

Notes: This table reports results of the two-factor asset-pricing model that comprises the DOL and AMI risk factors. We use as test assets five currency portfolios sorted based on past forward discounts (i.e., currency carry trade portfolios) and five tech-diffusion-sorted portfolios. We rebalance the portfolios on a monthly basis. Panel A reports Fama and MacBeth (1973) estimates of factor prices (λ). We also display Newey and West (1987) standard errors (in parentheses) corrected for autocorrelation and heteroskedasticity with the optimal lag selection. Sh represents the corresponding values of Shanken (1992). The table also shows the χ^2 and cross-sectional R^2. The number in the curly bracket is the *p-values* for χ^2. Panel B reports OLS estimates of contemporaneous time-series regression with HAC standard errors in parentheses. The alphas are annualized. We do not control for transaction costs, and excess returns are expressed in percentage points. The currency data are collected from Datastream *via* Barclays and Reuters and contain monthly series from January 1993 to December 2019.

Table B.6: Asset-Pricing for Subsamples before and after 2008

Panel A: Factor Prices Before 2008										
	λ_{DOL}	λ_{AMI}	χ^2	R^2	$RMSE$	λ_{DOL}	λ_{AMI}	χ^2	R^2	$RMSE$
	All Countries					**G10 Countries**				
GMM_1	2.38	21.47	3.60	0.67	1.45	1.34	10.73	3.65	0.52	1.29
	(2.18)	(15.29)	{0.31}			(2.13)	(4.71)	{0.30}		
GMM_2	2.07	27.96	3.18			1.48	13.25	3.46		
	(2.16)	(15.55)	0.36			(2.06)	(4.96)	{0.33}		
FMB	2.31	19.30	{13.37}			1.34	10.49	6.91		
(NW)	(1.82)	(5.56)	{0.01}			(1.74)	(3.65)	{0.14}		
(Sh)	(1.83)	(7.19)				(1.74)	(3.85)			

Panel B: Factor Prices After 2008										
	λ_{DOL}	λ_{AMI}	χ^2	R^2	$RMSE$	λ_{DOL}	λ_{AMI}	χ^2	R^2	$RMSE$
	All Countries					**G10 Countries**				
GMM_1	−2.28	3.06	1.89	0.51	0.61	−2.45	3.51	3.54	0.15	1.33
	(3.04)	(2.85)	{0.60}			(3.00)	(3.35)	{0.32}		
GMM_2	−2.29	3.04	3.18			−2.67	3.98	3.46		
	(2.94)	(2.76)	{0.36}			(2.87)	(3.18)	{0.33}		
FMB	−2.27	3.00	1.64			−2.43	3.21	2.73		
(NW)	(2.66)	(2.66)	{0.80}			(2.73)	(3.52)	{0.60}		
(Sh)	(2.66)	(2.70)				(2.73)	(3.56)			

Notes: This table reports results of the two-factor asset-pricing model when we divide our sample into two episodes. Panel A uses the subsample before the Global Finance Crisis (1/1993 - 12/2007); while panel B uses the subsample after it happened (1/2008 - 12/2019). We use as test assets five currency portfolios sorted based on past forward discounts (i.e., carry trade portfolios). We rebalance the portfolios on a monthly basis. The table reports GMM_1, GMM_2, and the Fama and MacBeth (1973)'s estimates of factor prices (λ). We also display Newey and West (1987) standard errors (in parentheses) corrected for autocorrelation and heteroskedasticity with the optimal lag selection. *Sh* represents the corresponding values of Shanken (1992). The table also shows the χ^2 and cross-sectional R^2. The numbers in curly brackets are *p-values* for the χ^2 tests.

Table B.7: Summary Statistics: Tech-Diffusion Portfolios Sorted on Half Samples: AMI and $UAMI$

	Panel A: Sorted on the First-Half-Sample Tech Diffusion											
	P_L	P_2	P_3	P_4	P_H	$UAMI$	P_L	P_2	P_3	P_4	P_H	$UAMI$
	All Countries						**G10 Currencies**					
	Log Excess Returns: rx^j						Log Excess Returns: rx^j					
Mean	7.13	2.87	7.21	7.99	10.78	3.65	4.97	1.49	5.96	7.67	9.78	4.81
	[2.04]	[0.93]	[2.49]	[2.80]	[3.30]	[1.93]	[1.47]	[0.44]	[2.31]	[2.57]	[2.88]	[2.56]
Sdev	8.56	7.03	7.64	7.47	8.28	5.26	8.38	7.81	7.17	8.22	8.76	5.53
SR	0.83	0.41	0.94	1.07	1.30	0.69	0.59	0.19	0.83	0.93	1.12	0.87
	Forward Discount: $f^j - s^j$						Forward Discount: $f^j - s^j$					
Mean	-0.15	-0.69	1.02	0.39	3.77	3.92	-1.00	-1.59	1.50	1.26	2.28	3.28
	[-3.10	[-3.82]	[5.20]	[4.72]	[6.09]	[25.94]	[-3.10]	[-3.82]	[5.20]	[4.72]	[6.09]	[25.94]
	Panel B: Sorted on Previous-Year Tech Diffusion											
	P_L	P_2	P_3	P_4	P_H	AMI	P_L	P_2	P_3	P_4	P_H	AMI
	Log Excess Returns: rx^j						Log Excess Returns: rx^j					
Mean	5.80	4.07	6.63	8.56	10.28	4.48	3.93	4.17	5.03	6.51	9.78	5.85
	[1.75]	[1.48]	[2.19]	[2.72]	[3.14]	[1.90]	[1.28]	[1.46]	[1.30]	[2.10]	[2.88]	[2.80]
Sdev	7.75	6.95	7.66	7.34	8.93	5.90	7.38	7.32	10.14	7.47	8.76	5.59
SR	0.75	0.59	0.87	1.17	1.15	0.76	0.53	0.57	0.50	0.87	1.12	1.05
	Forward Discount: $f^j - s^j$						Forward Discount: $f^j - s^j$					
Mean	-0.03	-0.10	0.43	0.93	3.24	3.27	-0.57	-0.28	-0.56	0.54	2.28	2.85
	[-0.10]	[-0.29]	[0.85]	[1.72]	[8.71]	[8.55]	[-3.76]	[-0.56]	[-1.05]	[1.25]	[6.09]	[8.73]

Notes: This table shows the summary statistics for quintile currency portfolios sorted on the average tech diffusion between 1/1993 and 1/2001 (panel A) and the previous-year tech diffusion (panel B). All the moments are calculated based on portfolio returns in the sample between 1/2001 to 12/2007. The first (last) portfolio P_L (P_H) comprise 20% of all currencies with the lowest (highest) value of tech-diffusion index. AMI and $UAMI$ are conditional and unconditional long-short strategies that buy P_H and sell P_L of portfolios. Moreover, the table presents the annualized mean, standard deviation (in percentage points), and Sharpe ratios. Figures in squared brackets represent Newey and West (1987) t-statistics corrected for heteroskedasticity and autocorrelation (HAC) using the optimal number of lags.

Table B.8: Asset-Pricing Tests for Unconditional Carry Portfolios: DOL and $UAMI$ Factors

Panel A: Factor Prices										
	λ_{DOL}	λ_{UAMI}	χ^2	R^2	$RMSE$	λ_{DOL}	λ_{UAMI}	χ^2	R^2	$RMSE$
	All Countries					**G10 Currencies**				
GMM_1	6.43	8.45	3.39	0.56	1.72	5.18	6.90	3.09	0.70	1.22
	(3.05)	(4.52)	{0.33}			(3.15)	(3.21)	{0.38}		
GMM_2	8.06	9.08	3.08			6.92	8.26	2.84		
	(2.67)	(3.92)	{0.38}			(2.68)	(3.01)	{0.42}		
FMB	6.39	7.55	7.59			5.16	6.66	7.15		
(NW)	(2.66)	(3.54)	{0.11}			(2.53)	(2.95)	{0.13}		
(Sh)	(2.67)	(3.83)				(2.53)	(3.06)			

Panel B: Factor Betas									
	α	β_{DOL}	β_{UAMI}	R^2		α	β_{DOL}	β_{UAMI}	R^2
P_L	0.13	0.89	−0.22	0.77	P_L	0.13	0.98	−0.37	0.83
	(0.09)	(0.05)	(0.08)			(0.07)	(0.05)	(0.08)	
P_2	0.42	0.92	−0.20	0.91	P_2	0.19	0.82	−0.32	0.89
	(0.07)	(0.03)	(0.04)			(0.06)	(0.02)	(0.02)	
P_3	0.53	1.23	−0.14	0.83	P_3	0.55	1.00	−0.08	0.85
	(0.10)	(0.06)	(0.10)			(0.08)	(0.05)	(0.05)	
P_4	0.70	1.01	0.42	0.76	P_4	0.57	1.25	0.27	0.88
	(0.11)	(0.07)	(0.08)			(0.10)	(0.06)	(0.08)	
P_H	0.92	1.28	0.05	0.82	P_H	0.69	0.99	0.38	0.79
	(0.12)	(0.07)	(0.09)			(0.10)	(0.05)	(0.08)	

Notes: This table reports results of the two-factor asset-pricing model that comprises the DOL and $UAMI$ risk factors. $UAMI$ stands for the (unconditional) return on a high-minus-low strategy sorted on the average tech-diffusion measure in the first half-sample between 1/1993 and 12/2000. We use as test assets the unconditional carry trade portfolios sorted on the first half-sample mean forward discount. The currency excess returns are calculated based on the second half-sample between 1/2001 and 12/2007.

Table B.9: Asset-Pricing for Double-Sort Factor: DOL and $AMI^{2\times3}$ factors

Panel A: Factor Prices										
	λ_{DOL}	$\lambda_{AMI^{2\times3}}$	χ^2	R^2	$RMSE$	λ_{DOL}	$\lambda_{AMI^{2\times3}}$	χ^2	R^2	$RMSE$
	All Countries					**G10 Currencies**				
GMM_1	−0.08	6.42	5.19	0.60	0.77	−0.48	5.72	3.06	0.70	0.76
	(1.76)	(2.57)	{0.16}			(1.70)	(2.35)	{0.38}		
GMM_2	−0.11	6.54	5.19			−0.51	6.77	3.03		
	(1.74)	(2.43)	{0.16}			(1.66)	(2.28)	{0.39}		
FMB	−0.08	6.33	6.37			−0.48	5.67	3.20		
(NW)	(1.49)	(2.13)	{0.17}			(1.44)	(2.22)	{0.52}		
(Sh)	(1.49)	(2.17)				(1.44)	(2.25)			

Panel B: Factor Betas									
	α	β_{DOL}	$\beta_{AMI^{2\times3}}$	R^2		α	β_{DOL}	$\beta_{AMI^{2\times3}}$	R^2
P_L	−0.20	0.99	−0.27	0.78	P_L	−0.19	0.88	−0.37	0.72
	(0.06)	(0.05)	(0.07)			(0.07)	(0.05)	(0.05)	
P_2	−0.09	1.03	−0.12	0.81	P_2	−0.14	0.96	−0.12	0.75
	(0.05)	(0.05)	(0.04)			(0.06)	(0.04)	(0.04)	
P_3	0.08	1.00	−0.07	0.85	P_3	0.08	0.93	0.05	0.56
	(0.05)	(0.04)	(0.03)			(0.09)	(0.06)	(0.06)	
P_4	0.01	1.03	0.12	0.82	P_4	−0.05	1.08	0.17	0.74
	(0.06)	(0.04)	(0.05)			(0.07)	(0.06)	(0.05)	
P_H	0.21	1.19	0.41	0.89	P_H	0.19	1.27	0.45	0.83
	(0.06)	(0.04)	(0.06)			(0.06)	(0.05)	(0.05)	

Notes: This table reports results of the two-factor asset-pricing model that comprises DOL and $AMI^{2\times3}$ risk factors. $AMI^{2\times3}$ is the currency risk factor based on a double-sorting strategy. We use as test assets five currency portfolios sorted based on past forward discounts (i.e., carry trade portfolios). We rebalance the portfolios on a monthly basis. Panel A reports GMM_1, GMM_2 as well as Fama and MacBeth (1973) estimates of factor prices of risk (λ). We also display Newey and West (1987) standard errors (in parentheses) corrected for autocorrelation and heteroskedasticity with optimal lag selection. Panel B reports OLS estimates of contemporaneous time-series regression with HAC standard errors in parentheses. The currency data are collected from Datastream *via* Barclays and Reuters and contain monthly series from January 1993 to December 2019.

Table B.10: Correlation b/w Alternative Risk Factors

	HML^{FX}	AMI	IMX	$PMC^{(-)}$	$AMI^{2\times3}$
HML^{FX}	1.00				
AMI	0.52	1.00			
IMX	0.64	0.62	1.00		
$PMC^{(-)}$	0.53	0.53	0.60	1.00	
$AMI^{2\times3}$	0.59	0.70	0.59	0.40	1.00

Notes: This table presents the correlation matrix between alternative risk factors. $PMC^{(-)}$ is the currency risk factor sorted based on previous-year trade network centrality (as in Richmond, 2019) and goes long in the central countries and short in the peripheral countries (the reverse of PMC). IMX is the currency factor sorted based on previous-year import ratio (as in Ready et al., 2017) and goes long in the high-import-ratio currencies (commodity country) and short in the low-import-ratio currencies (producer country). HML^{FX} is the conditional carry factor. $AMI^{2\times3}$ is the double-sorting strategy based on the R&D ratio and trade concentration. We use the sample of 22 countries as in Ready et al. (2017).

Table B.11: Cross-Sectional Asset-Pricing using RRW's Sample of 22 Countries (Ready et al., 2017)

Panel A: Factor Prices					
	λ_{DOL}	λ_{AMI}	χ^2	R^2	$RMSE$
GMM_1	−0.22	6.73	2.02	0.84	0.47
	(1.71)	(2.73)	{0.57}		
GMM_2	−0.26	7.96	1.99		
	(1.69)	(2.79)	{0.57}		
FMB	−0.22	6.68	2.17		
(NW)	(1.46)	(2.44)	{0.70}		
(Sh)	(1.46)	(2.53)	{0.74}		

Panel B: Factor Betas				
	α	β_{DOL}	β_{AMI}	R^2
P_L	−0.17	0.87	−0.33	0.62
	(0.08)	(0.07)	(0.07)	
P_2	−0.16	0.99	−0.14	0.84
	(0.04)	(0.03)	(0.04)	
P_3	0.01	0.97	−0.02	0.80
	(0.05)	(0.03)	(0.03)	
P_4	−0.01	1.01	0.08	0.81
	(0.06)	(0.04)	(0.06)	
P_H	0.20	1.17	0.36	0.82
	(0.07)	(0.04)	(0.08)	

Notes: This table reports results of the two-factor asset-pricing model that comprises DOL and AMI risk factors. We use as test assets five currency portfolios sorted based on past forward discounts (i.e., carry trade portfolios). We rebalance the portfolios on a monthly basis. Panel A reports GMM_1, GMM_2, and Fama and MacBeth (1973)'s estimates of factor prices (λ). We also display Newey and West (1987) standard errors (in parentheses) corrected for autocorrelation and heteroskedasticity with optimal lag selection. *Sh* are the corresponding values of Shanken (1992). The table also shows the χ^2 and cross-sectional R^2. The numbers in curly brackets are *p-values* for the pricing error test. Panel B reports OLS estimates of contemporaneous time-series regression with HAC standard errors in parentheses. The alphas are annualized. The currency data are collected from Datastream *via* Barclays and Reuters and contain monthly series from January 1993 to December 2019.

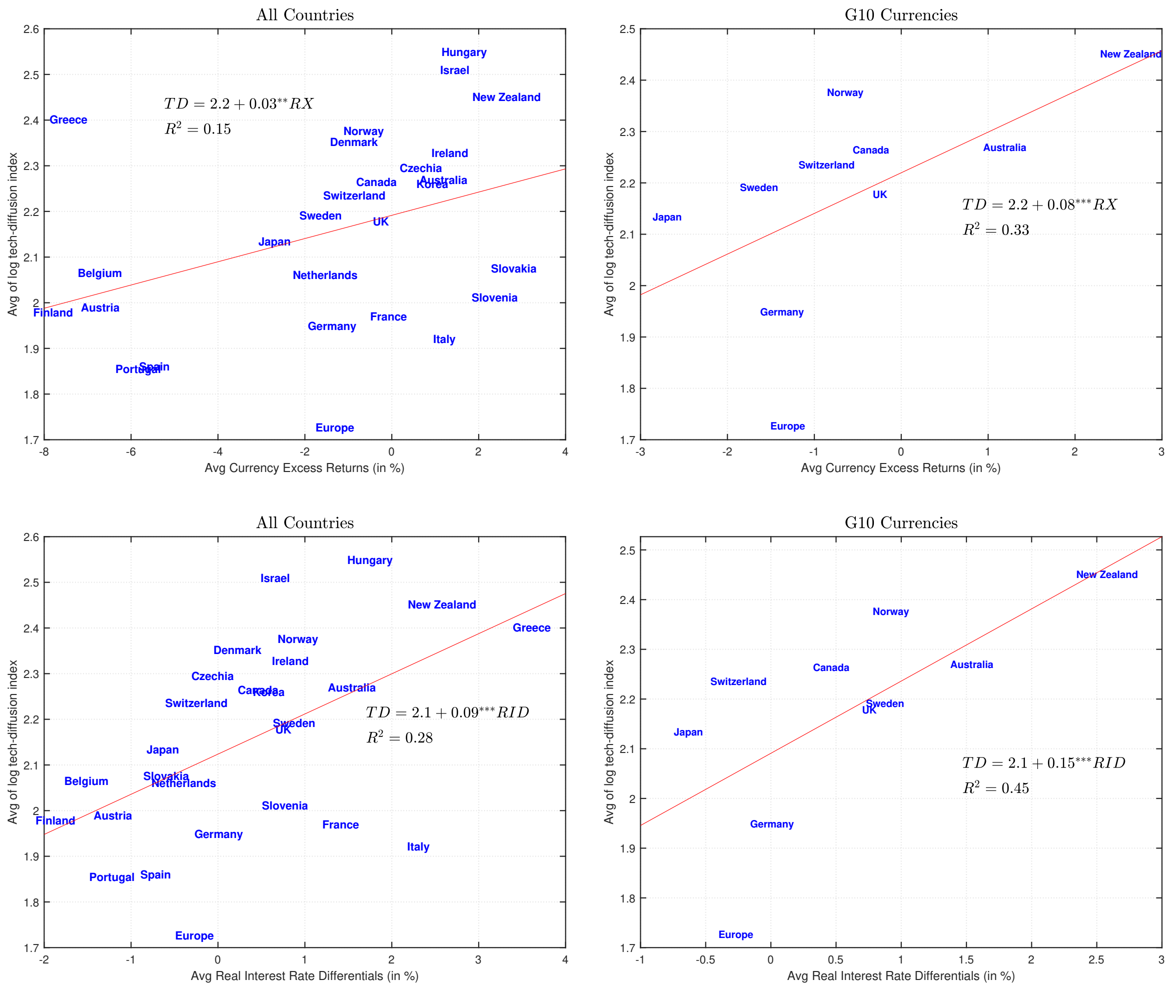
Table B.12: Conditional Asset-Pricing Using Rolling-Window Regressions

Panel A: **All Countries**					
λ_{DOL}	λ_{AMI}	$\chi^2(NW)$	$\chi^2(Sh)$	$RMSE$	$\rho(\lambda_{AMI,t}, HML_t^{FX})$
-0.62	4.39	12.90	4.85	1.14	0.48
(1.54)	(1.82)	{0.06}	{0.45}		
Panel B: **G10 Currencies**					
λ_{DOL}	λ_{AMI}	$\chi^2(NW)$	$\chi^2(Sh)$	$RMSE$	$\rho(\lambda_{AMI,t}, HML_t^{FX})$
-0.91	2.43	12.52	4.92	1.36	0.77
(1.51)	(1.94)	{0.12}	{0.47}		

Notes: The table reports the results of the Fama-Macbeth rolling-window asset-pricing test based on 36-months windows. The numbers are the market prices of risk, the root-mean-square errors (RMSE), and the χ^2 of pricing-error tests together with the p-values. Test assets are the five currency portfolios sorted on the previous-month forward discounts. The standard errors in parentheses are based on Newey and West (1987). The sample period covers from January 1993 to December 2019.

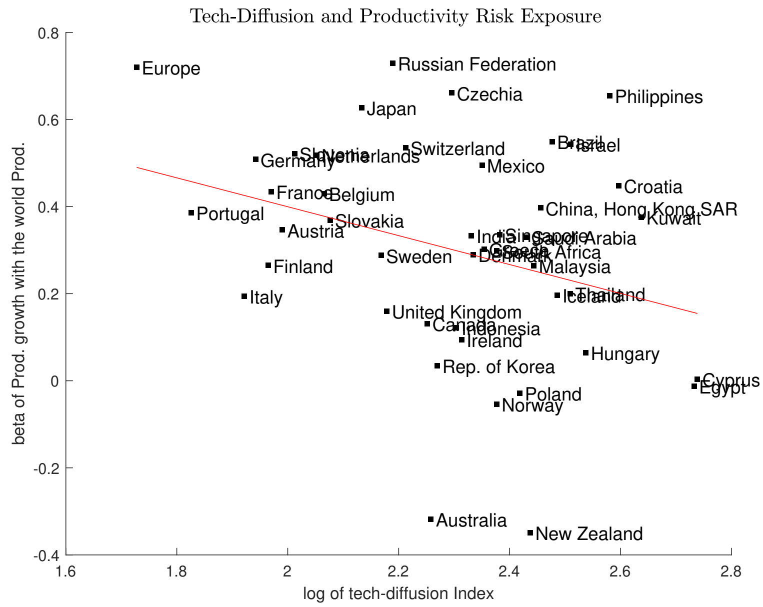
C Additional Figures

Figure C.1: Tech Diffusion, Real Interest Rate Differentials, and Currency Excess Returns



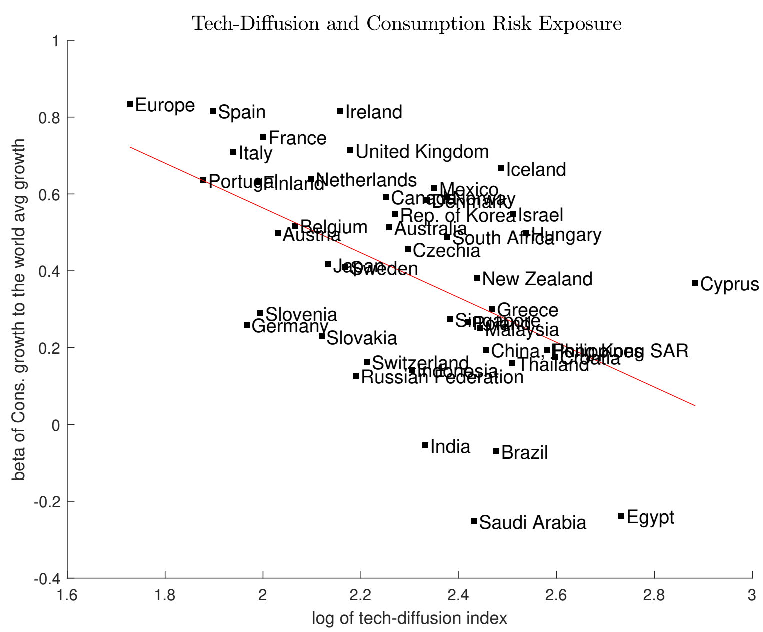
Notes: The graph shows the average tech-diffusion indexes (TD) for our sample countries against their average excess returns (referred to as RX) and real interest rate differentials (relative to the U.S., referred to as RID). The left panel reports results for "All Countries", while the right panel shows results for "G10 Currencies". The real interest rate is calculated using the three-month forward discounts subtracted by the four-quarter moving average of inflation of each country.

Figure C.2: Tech Diffusion vs. Productivity Risk Exposure β_i^z: A Broader Set of Countries



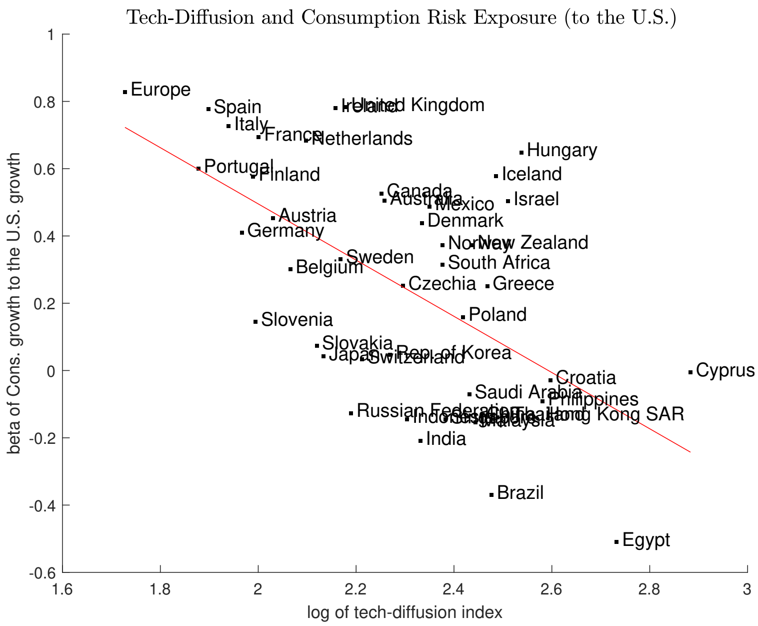
Notes: The figure shows the productivity growth betas against the average tech-diffusion measure (TD) for a broader set of countries. See the description under figure 2 for construction of productivity growth betas.

Figure C.3: Tech Diffusion vs. Consumption Risk Exposure β_i^c: A Broader Set of Countries



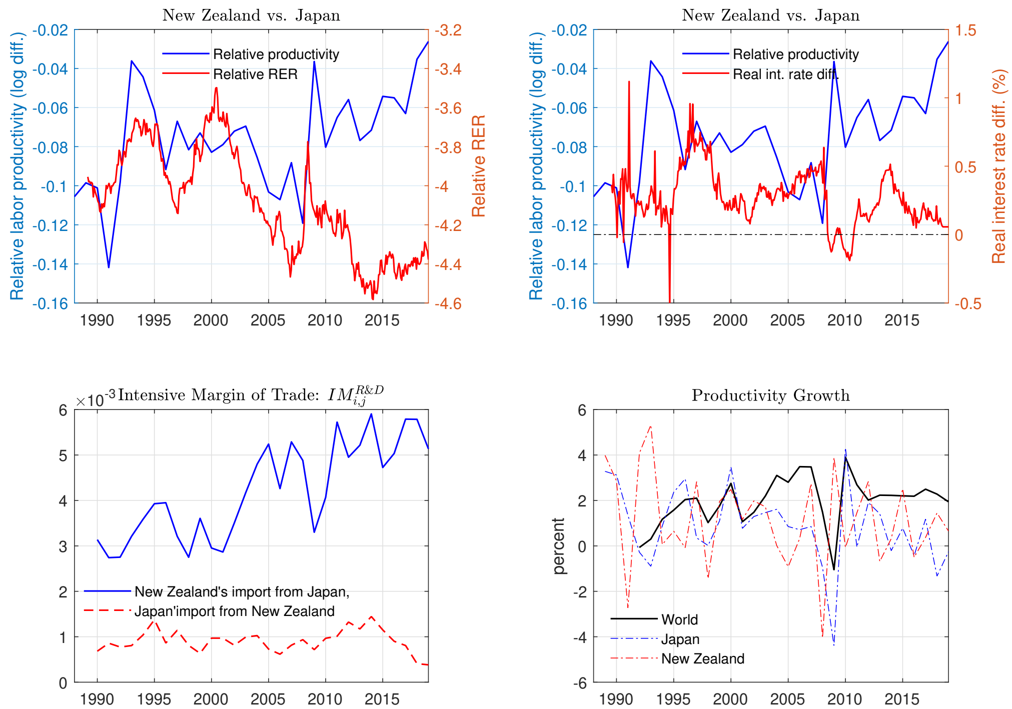
Notes: The figure shows the consumption growth betas against the average tech-diffusion measure (TD) for a broader set of countries. See the description under under figure 2 for construction of consumption growth betas.

Figure C.4: Tech Diffusion vs. Consumption Exposure to the U.S.: $\beta_i^{c,US}$



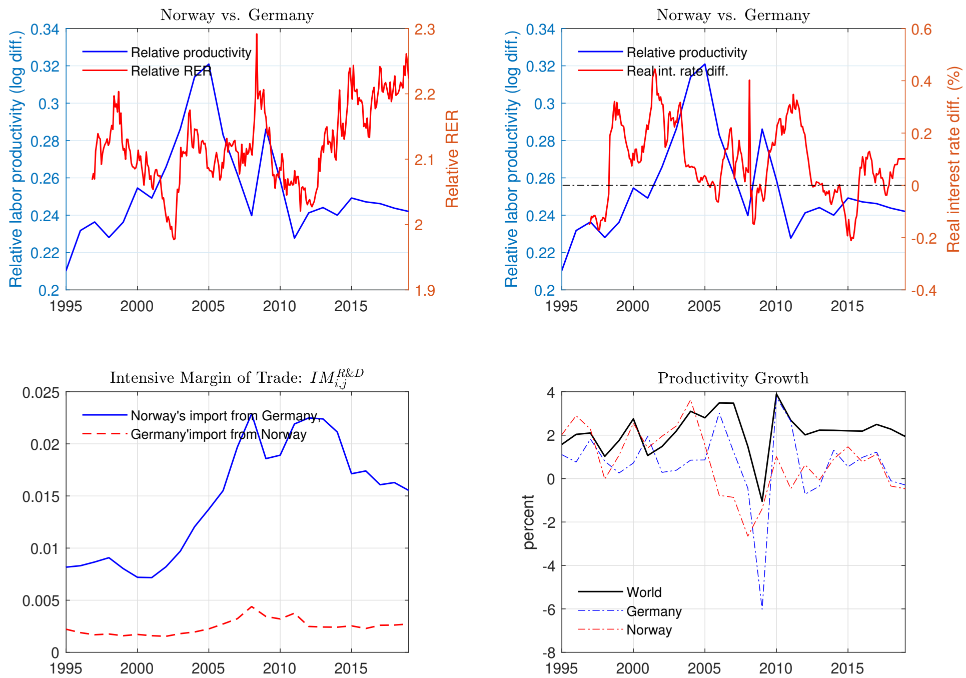
Notes: The figure plots the consumption risk exposure to the U.S. economy against their tech-diffusion measures (TD). Each country's consumption risk exposure to the U.S. economy is calculated based on the following regression: $\Delta\text{Consumption}_{i,t} = \alpha_i + \beta_i^{c,US} \times \Delta\text{US Consumption}_t + \varepsilon_{i,t}$.

Figure C.5: Relative Productivity, Real Exchange Rate, and Interest Rate Differentials: New Zealand versus Japan



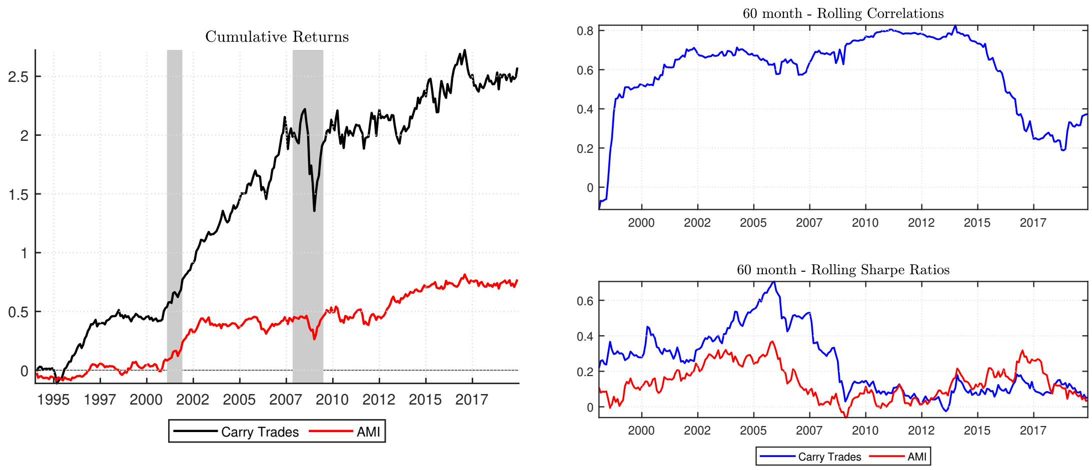
Notes: The figure shows the time series of productivities, the relative real exchange rates, real interest rate differentials, and R&D content of imports (intensive margin) for a pair of high and low-tech-diffusion countries. In the bottom left panel, the classification of high-technology goods is based on the UN's SITC code of manufacturing products. New Zealand is considered a high-tech-diffusion country, while Japan is New Zealand's major trading partner aside from the eurozone.

Figure C.6: Relative Productivity, Real Exchange Rate, and Interest Rate Differentials: Norway versus Germany



Notes: The figure shows the time series of productivities, the relative real exchange rates, real interest rate differentials, and R&D content of imports (intensive margin) for a pair of high and low-tech-diffusion countries. In the bottom left panel, the classification of high-technology goods is based on the UN's SITC code of manufacturing products. Norway is considered a high-tech-diffusion country, while Germany is Norway's largest trading partner. We use the euro exchange rate after Germany joined the eurozone in 1999.

Figure C.7: Cumulative Returns and Rolling-Window Statistics (**All Countries**)



Notes: The left panel displays the cumulative returns from the carry trade and tech-diffusion-sorted (AMI) portfolios. The right panel displays (60-month) rolling-window correlations of the carry and AMI portfolios as well as their rolling-window Sharpe ratios. The data contain monthly series from January 1993 to December 2019. The results are based on the group of "All Countries."

Figure C.8: Number of Available Currencies

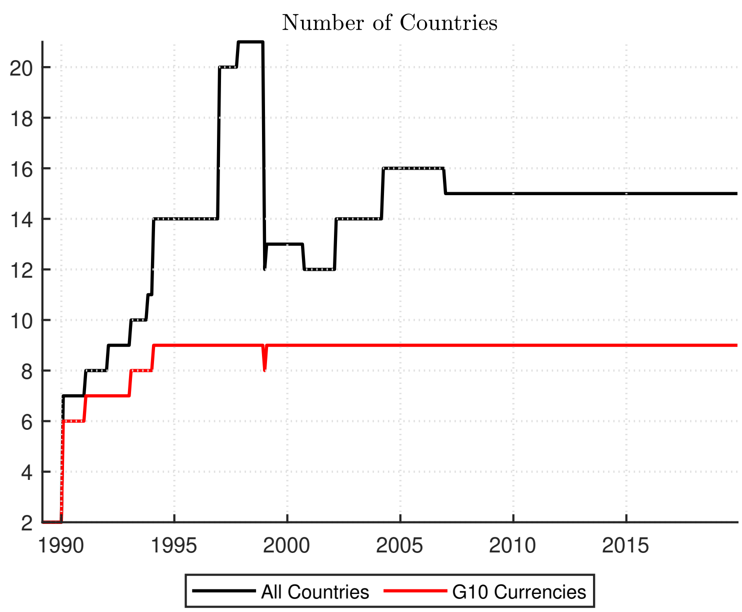
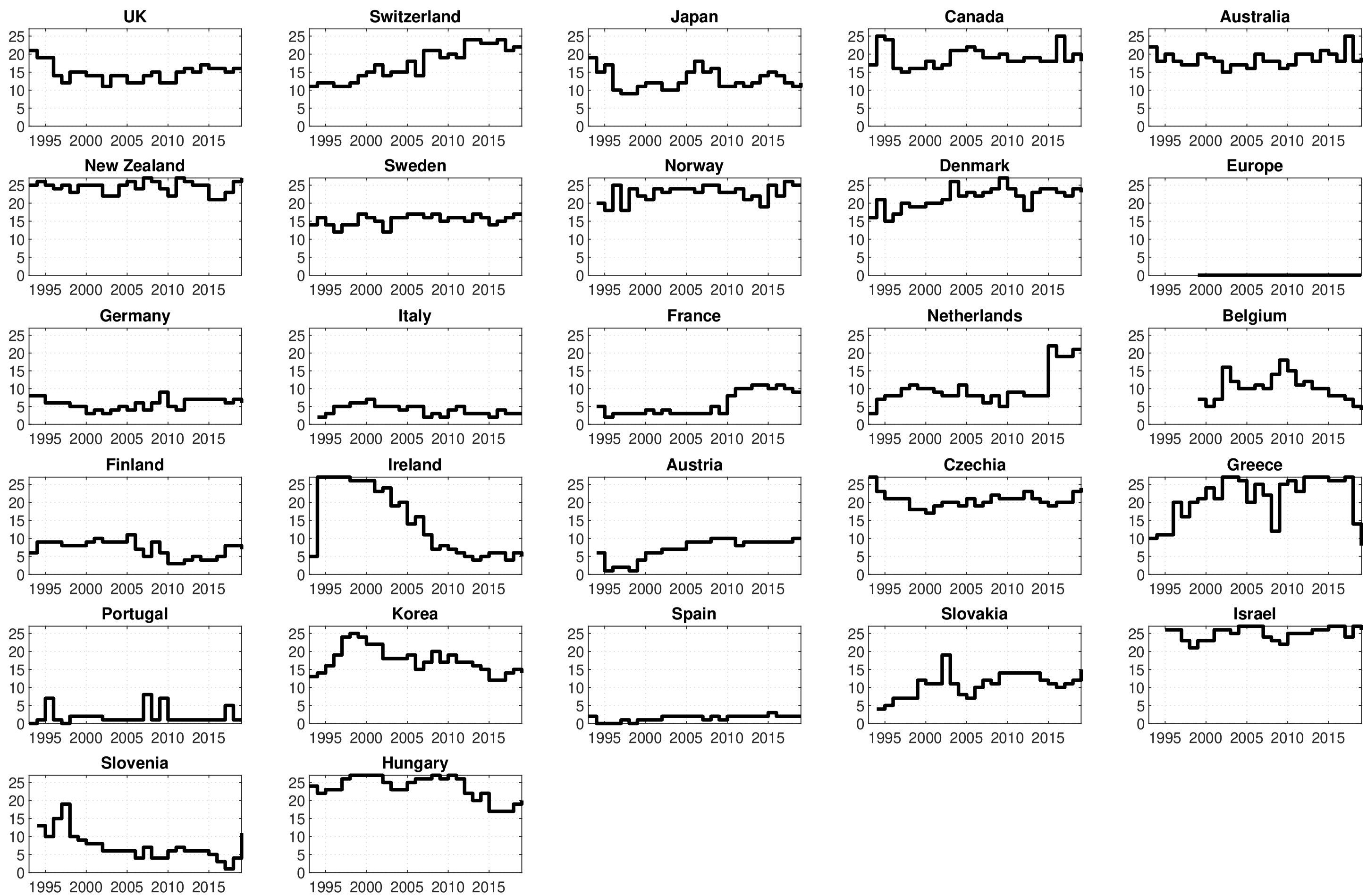
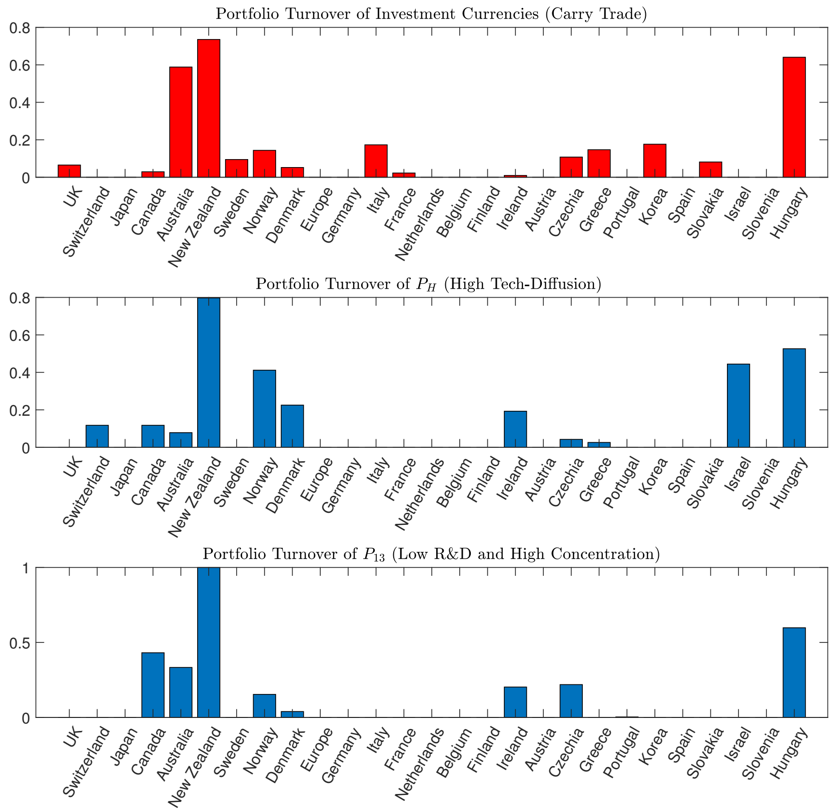


Figure C.9: Ranking of Tech-Diffusion Measures (TD)



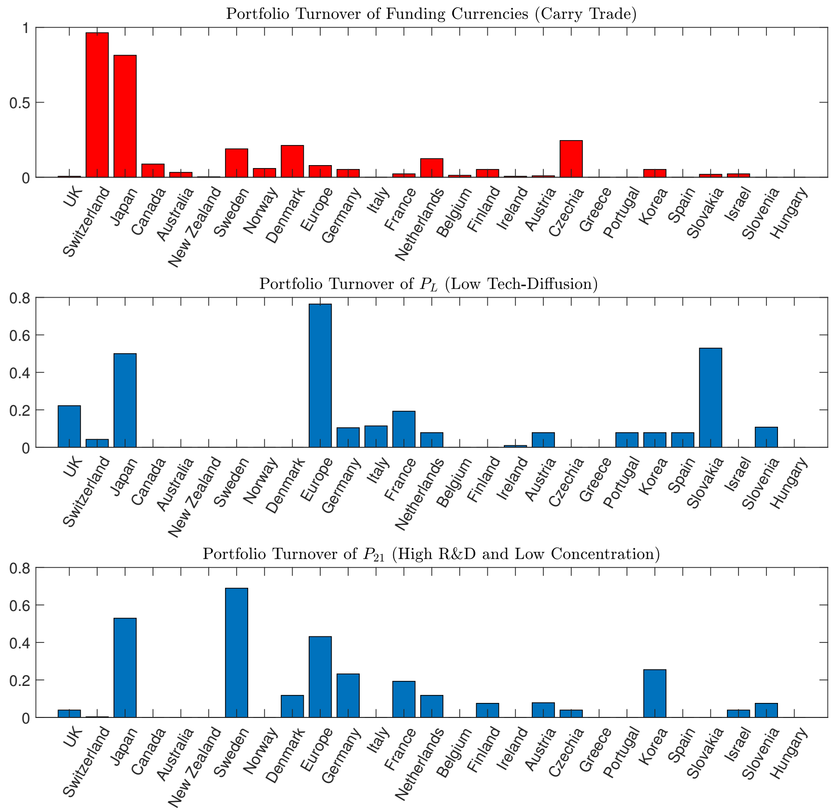
Notes: The figure displays the ranking of each country's tech-diffusion measure. Rankings are normalized each month to between 1 and 27, the maximum number of currencies in our sample. The data are collected from Datastream *via* Barclays and Reuters, which contain monthly series from January 1993 to December 2019.

Figure C.10: Portfolio Turnover of Investment Currencies (**All Countries**)



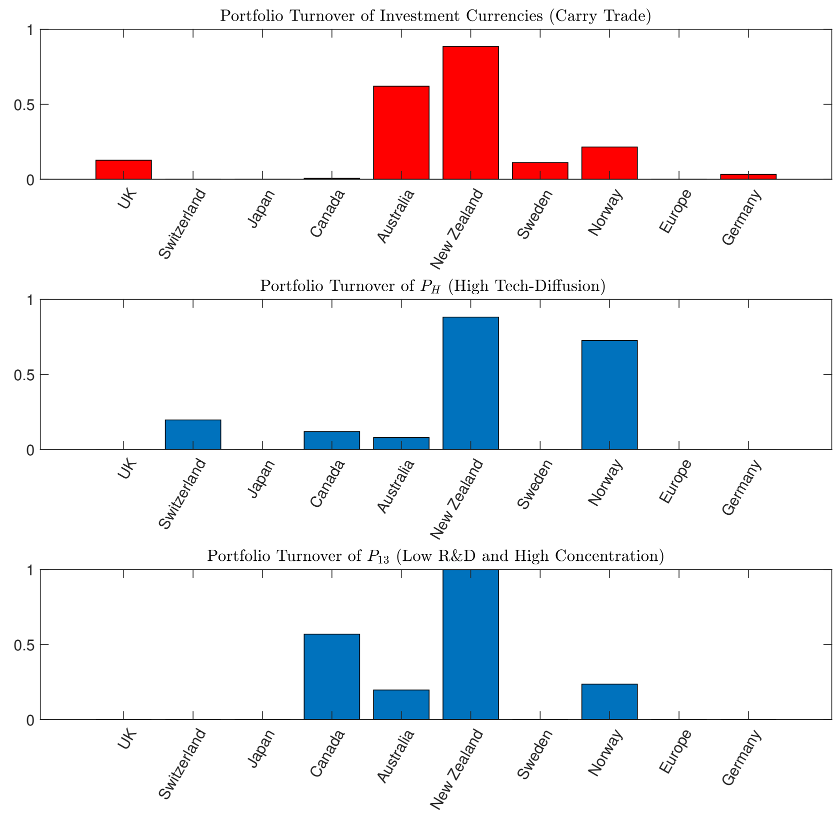
Notes: The figure displays turnover rates of the carry trade portfolio (upper panel), tech-diffusion-sorted portfolio (middle panel), and portfolio constructed by double-sorting strategy (bottom panel). The results are based on the sample of all countries. A larger number means that a country more frequently belongs to the investment currency group. The data are collected from Datastream *via* Barclays and Reuters, which contain monthly series from January 1993 to December 2019.

Figure C.11: Portfolio Turnover of Funding Currencies (**All Countries**)



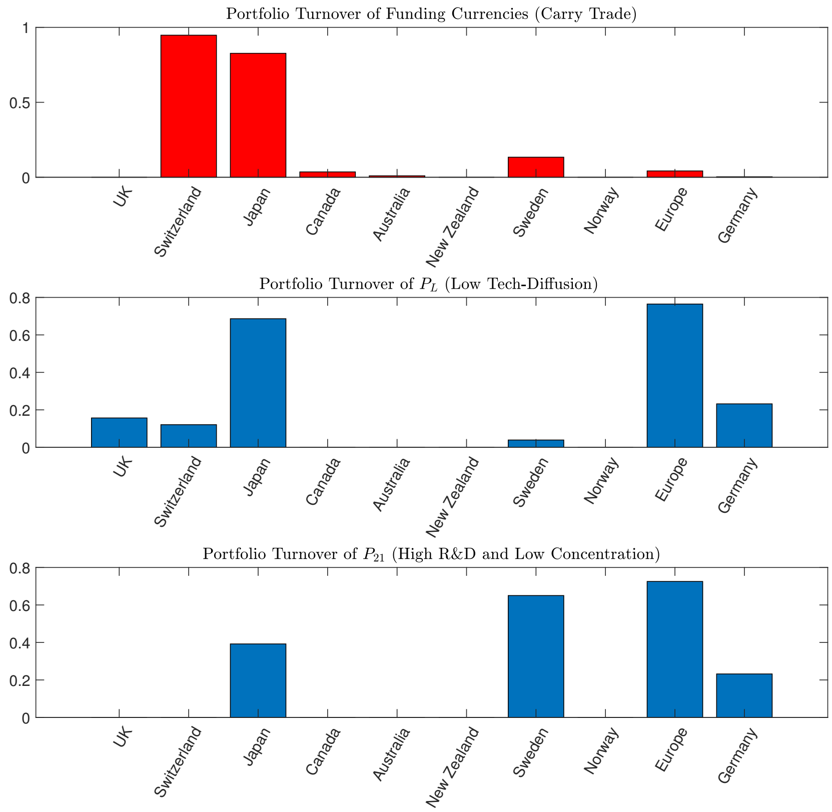
Notes: The figure displays turnover rates of the carry trade portfolio (upper panel), tech-diffusion-sorted portfolio (middle panel), and portfolio constructed by double-sorting strategy (bottom panel). The results are based on the sample of all countries. A larger number means that a country more frequently belongs to the funding currency group. The data are collected from Datastream *via* Barclays and Reuters, which contain monthly series from January 1993 to December 2019.

Figure C.12: Portfolio Turnover of Investment Currencies (**G10 Currencies**)



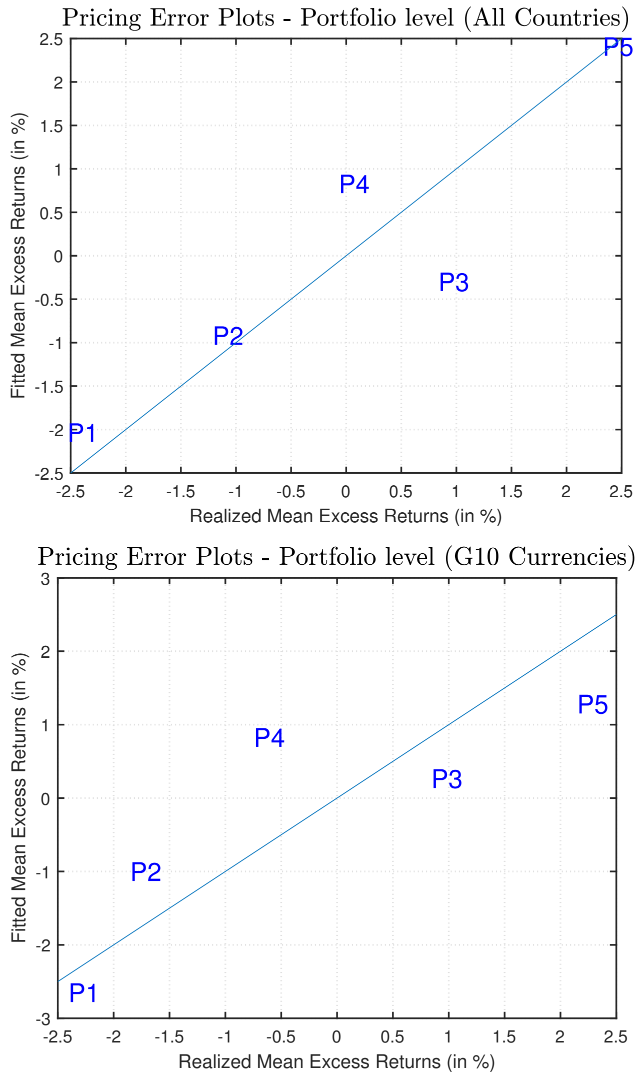
Notes: The figure displays turnover rates of the carry trade portfolio (upper panel), tech-diffusion-sorted portfolio (middle panel), and portfolio constructed by double-sorting strategy (bottom panel). The results are based on the sample of G10 currencies. A larger number means that a country more frequently belongs to the investment currency group. The data are collected from Datastream *via* Barclays and Reuters, which contain monthly series from January 1993 to December 2019.

Figure C.13: Portfolio Turnover of Funding Currencies (**G10 Currencies**)



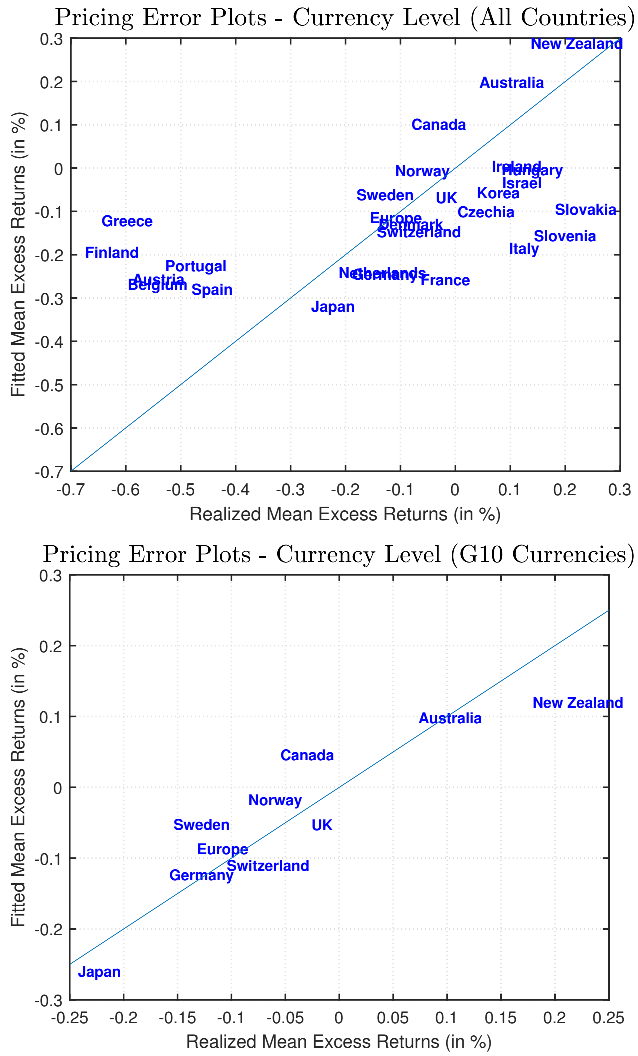
Notes: The figure displays turnover rates of the carry trade portfolio (upper panel), tech-diffusion-sorted portfolio (middle panel), and portfolio constructed by double-sorting strategy (bottom panel). The results are based on the sample of G10 currencies. A larger number means that a country more frequently belongs to the funding currency group. The data are collected from Datastream *via* Barclays and Reuters, which contain monthly series from January 1993 to December 2019.

Figure C.14: Pricing Error Plot: Portfolio-Level Asset Pricing



Notes: The figure plots the fitted currency excess returns based on our asset-pricing model against the realized mean excess returns for each quintile portfolio.

Figure C.15: Pricing Error Plot: Currency-Level Asset Pricing

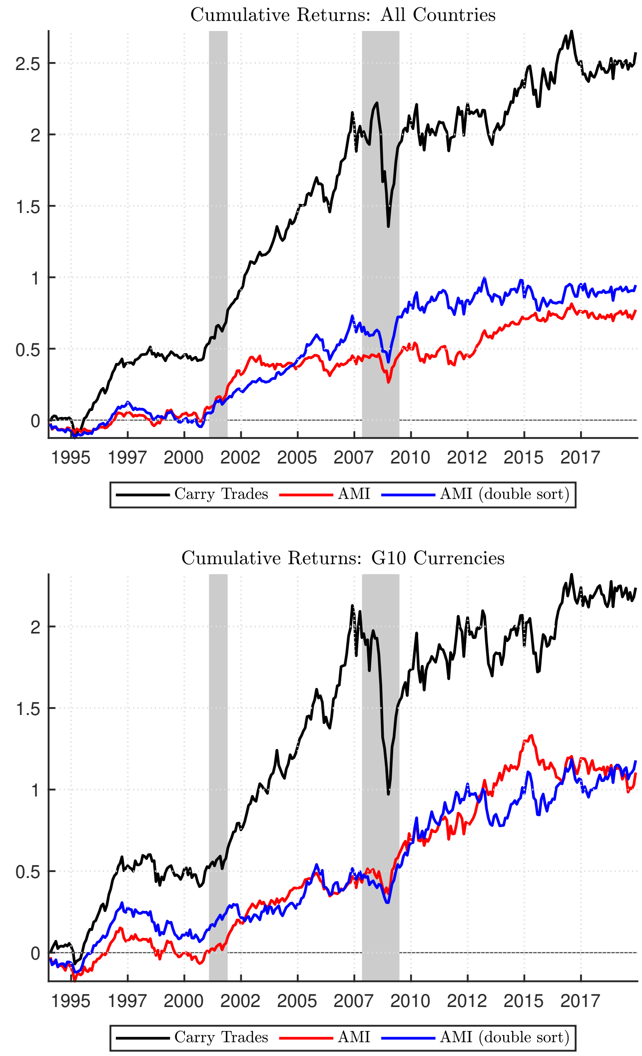


Notes: The figure plots the pricing errors for the currency-level asset pricing. First, we run a time-series regression of currency return $rx_{j,t}$ on DOL_t and AMI_t factors (with a constant). Then, we run the cross-sectional regression, period by period, to get the estimates of factor price: λ_{DOL} and λ_{AMI}. The horizontal axis represents the realized mean excess return ($\overline{rx}_j$) for each currency, while the vertical axis shows the fitted excess returns based on our asset-pricing model; that is $\widehat{rx}_j = \beta_j \lambda$.

Figure C.16: An Illustration of the Double-Sorting Strategy

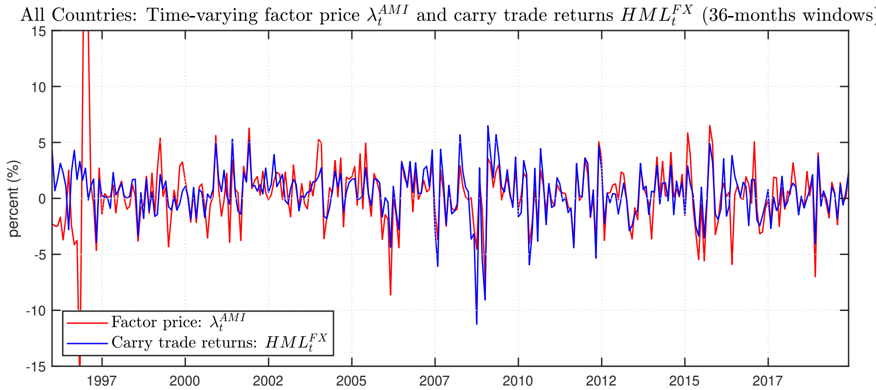
	low TC	medium TC	high TC
low $R\&D$	P_{11} (10%)	P_{12} (10%)	P_{13} (20%)
high $R\&D$	P_{21} (20%)	P_{22} (10%)	P_{23} (10%)

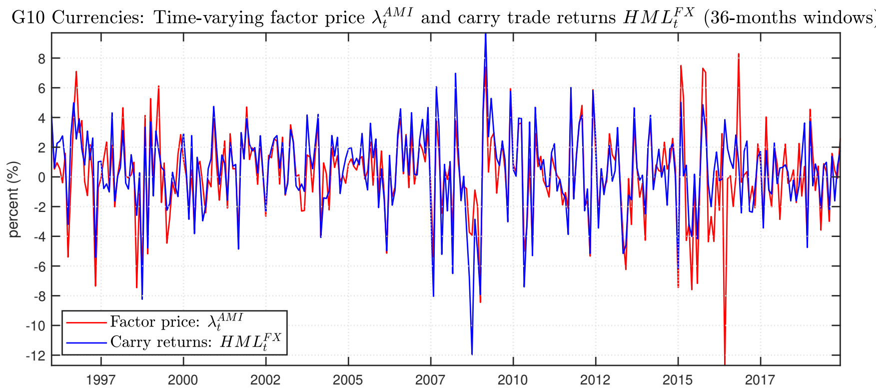
Figure C.17: Cumulative Returns: Tech-Diffusion and Double-Sorting Strategies



Notes: The figure compares the cumulative returns of tech-diffusion-sorted portfolio (AMI) and double-sort portfolio ($AMI^{2\times3}$). The upper panel shows the group of "All Countries", while the lower panel shows "G10 Currencies". The data contain monthly series from January 1993 to December 2019.

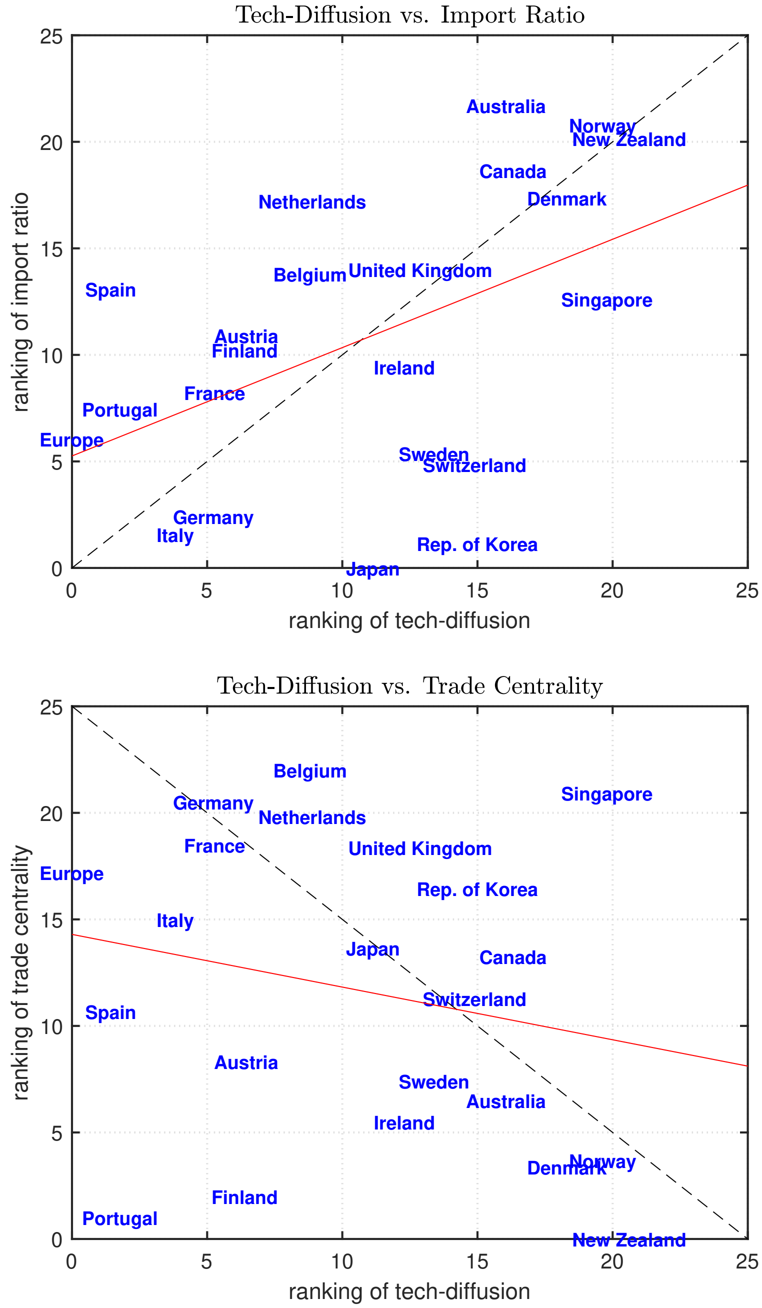
Figure C.18: Time-Varying Factor Prices ($\lambda_{AMI,t}$) and Carry Trade Returns





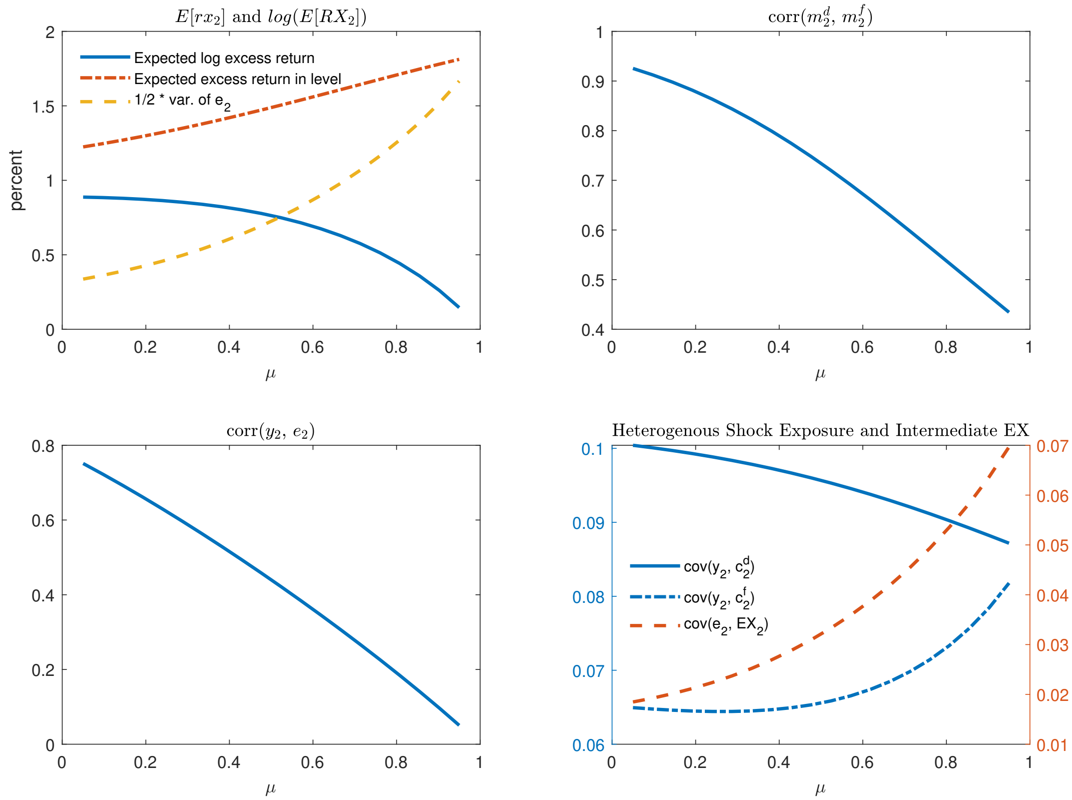
Notes: This figure shows the time-varying factor prices of tech diffusion ($\lambda_{AMI,t}$) based on the conditional FMB regression. First, we calculate the betas (β_t^j) of each portfolio by running a time-series regression of portfolio excess return on the DOL and AMI factors (using 36-month windows). Second, in each period, we run a cross-sectional regression of the average portfolio return over the event window $\overline{rx}_t^j = \left(\sum_{s=t-36}^{t} rx_s^j\right)/36$ on portfolio betas β_t^j. The figure compares the paths of slope coefficients ($\lambda_{AMI,t}$) with the carry trade returns (HML_t^{FX}).

Figure C.19: Comparing Alternative Currency Risk Factors: Tech Diffusion, Trade Centrality, and Import Ratio



Notes: This figure compares the countries' average ranking based on our tech-diffusion factor versus alternative currency risk factors in the literature, which includes import ratio (as in Ready et al., 2017) and trade centrality (as in Richmond, 2019). The import ratio is defined as the net export of basic goods minus net exports of complex goods as a percentage of total trade volumes. Centrality is the export-share weighted average of countries' bilateral trade intensities — pairwise trade divided by pairwise total GDP.

Figure C.20: Simulated Model Moments by Varying the Size of Adoption Sector $(1-\mu)$



NOTE: This picture shows model-implied moments by varying the size of adoption sector: $1-\mu$. Other parameter values are described under figure 7. And we set the correlation of productivity shocks $\rho_{df} = 0.4$.

Online Appendix

Technology Diffusion and Currency Risk Premia

A Extension of Theoretical Model

A.1 Decentralized Economy

In this section, we prove that the social planner's setup is the main text can be decentralized as the competitive equilibrium in a two-country innovation model. The model consists of the following components.

Final Good Packagers. The final good packagers use the labor and intermediate goods to produce the final consumption goods. In the home country, the profit maximization problem is

$$\max_{x_{2,i}^h} \left\{ y_2^h - \sum_{i=1}^{N_2^h} P_{2,i}^h x_{2,i}^h - w_2^h l_2^h \right\}, \qquad s.t. \quad y_2^h = z^h \left(\sum_{i=1}^{N_2^h} x_{2,i}^{h,\xi} \right) l_2^{h,1-\xi}.$$

In the foreign country, the problem is

$$\max_{x_{2,i}^f, x_{h,2,j}^f} \left\{ y_2^f - \sum_{i=1}^{N_2^f} P_{2,i}^f x_{2,i}^f - \sum_{j=1}^{N_{h,2}^f} P_{h,2,j}^f x_{h,2,j}^f - w_2^f l_2^f \right\},$$
$$s.t. \quad y_2^f = z^f \left[\mu^{1-\xi} \sum_{i=1}^{N_2^f} x_{2,i}^{f,\xi} + (1-\mu)^{1-\xi} \sum_{j=1}^{N_{h,2}^f} x_{h,2,j}^{f,\xi} \right] l_2^{f,1-\xi}.$$

The first-order conditions consist of a list of downward-sloping demand functions for intermediate goods,

$$P_{2,i}^h = \xi z^h x_{2,i}^{h,\xi-1}, \quad \text{for} \quad i = 1, 2, \cdots, N_2^h$$
$$P_{2,i}^f = \mu^{1-\xi} \xi z^f x_{2,i}^{f,\xi-1}, \quad \text{for} \quad i = 1, 2, \cdots, N_2^f$$
$$P_{h,2,j}^f = (1-\mu)^{1-\xi} \xi z^f x_{h,2,i}^{f,\xi-1}, \quad \text{for} \quad j = 1, 2, \cdots, N_{h,2}^f,$$

and equilibrium wage rate,

$$w_2^h = (1-\xi) \frac{y_2^h}{l_2^h}, \qquad w_2^f = (1-\xi) \frac{y_2^f}{l_2^f}. \tag{C.1}$$

Intermediate Good Producers. The intermediate good producers use the final goods to produce intermediate goods subject to the given demand schedules. To eliminate the monopolistic power, we assume that each producer faces a proportional subsidy on its production cost: $\tau = 1-\xi$. Specifically, for an innovated factory plant in country-H, the producer maximizes the following objective function:

$$\pi_2^h = \max_{x_2^h} \left\{ P_2^h(x_2^h)x_2^h - x_2^h(1-\tau) \right\}.$$

Similarly, an innovated factory plant in country-F solves the following problem:

$$\pi_2^f = \max_{x_2^f} \left\{ P_2^f(x_2^f)x_2^f - x_2^f(1-\tau) \right\}.$$

Meanwhile, an adopted factory plant in country-F solves:

$$\pi_{h,2}^f = \max_{x_{h,2}^f} \left\{ P_{h,2}^f(x_{h,2}^f)x_{h,2}^f - x_{h,2}^f \frac{1}{e_2}(1-\tau) \right\},$$

where the exchange rate term indicates that an adopted factory must use imported materials to produce intermediate goods. Then, we have the following optimal intermediate input and profit functions,

$$x_2^{h*} = \xi^{\frac{1}{1-\xi}} z^{h,\frac{1}{1-\xi}}, \quad x_2^{f*} = \xi^{\frac{1}{1-\xi}} z^{f,\frac{1}{1-\xi}} \mu, \quad x_{h,2}^{f*} = \xi^{\frac{1}{1-\xi}} z^{f,\frac{1}{1-\xi}} e_2^{\frac{1}{1-\xi}} (1-\mu), \tag{C.2}$$

$$\pi_2^{h*} = \xi\tilde{\xi} z^{h,\frac{1}{1-\xi}}, \quad \pi_2^{f*} = \xi\tilde{\xi} z^{f,\frac{1}{1-\xi}} \mu, \quad \pi_{h,2}^{f*} = \xi\tilde{\xi} z^{f,\frac{1}{1-\xi}} e_2^{\frac{\xi}{1-\xi}} (1-\mu). \tag{C.3}$$

where $\tilde{\xi} = \xi^{\frac{\xi}{1-\xi}} - \xi^{\frac{1}{1-\xi}}$.

We assume the labor supply in both countries equals to 1. Taking the intermediate inputs into the production function gives us the final output functions,

$$y_2^{h*} = z^{h,\frac{1}{1-\xi}} \xi^{\frac{\xi}{1-\xi}} N^h, \tag{C.4}$$

$$y_2^{f*} = z^{f,\frac{1}{1-\xi}} \xi^{\frac{\xi}{1-\xi}} \left(\mu N_2^f + (1-\mu) N_{h,2}^f e_2^{\frac{\xi}{1-\xi}} \right). \tag{C.5}$$

Innovators & Adopters. We assume there is one innovator in each country. The foreign-country innovator decides the number of invented patents only based on profits made on its local market ($\Pi_2^{FI} = N_2^f \pi_2^{f*}$). However, the home country makes innovation decisions based on both the local production profits ($\Pi_2^{HI} = N_2^h \pi_2^{h*}$) and the profits by outsourcing technology to the foreign country ($\Pi_2^{FA} = N_{h,2}^f \pi_{h,2}^{f*}$). After the home country decides the number of patents to be invented, the foreign country decides its adopted proportion.

In the first period, the foreign-country innovator solves the following problem:

$$\max_{N_2^f} \left\{ \frac{\lambda_2^f}{\lambda_1^f} N_2^f \pi_2^{f*} - F_f(N_2^f) \right\} \tag{C.6}$$

where $\frac{\lambda_2^f}{\lambda_1^f}$ denotes the foreign country's pricing kernel. In the meanwhile, the foreign-country adopter solves:

$$\max_{N_{h,2}^f} \left\{ \frac{\lambda_2^f}{\lambda_1^f} N_{h,2}^f \pi_{h,2}^{f*} - F_{hf}(N_2^{h,f}, N_2^h) \right\}. \tag{C.7}$$

On the other hand, the home-country innovator decides the number of patents by taking into consideration the profits made by foreign adoption. The problem is given by the following,

$$\max_{N_2^h} \left\{ \frac{\lambda_2^h}{\lambda_1^h} N_2^h \pi_2^{h*} + e_1 \left[\frac{\lambda_2^f}{\lambda_1^f} N_{h,2}^f \pi_{h,2}^{f*} - F_{hf}(N_2^{h,f}, N_2^h) \right] - F_h(N_2^h) \right\}. \tag{C.8}$$

where $\frac{\lambda_2^h}{\lambda_1^h}$ denotes the home country's pricing kernel. We embed the foreign adopter's franchise value into the home innovator's problem after converting it to the home currency.

The innovator and adopter's optimal investment decisions are characterized by the first-order conditions:

$$\bar{\chi}(1+\eta)(N_2^f)^\eta = \frac{\lambda_2^f}{\lambda_1^f} \xi \tilde{\xi} z^{f,\frac{1}{1-\xi}} \mu, \tag{C.9}$$

$$\chi^a b_1 \exp^{\{b_1 N_{h,2}^f - b_2 N_2^h\}} = \frac{\lambda_2^f}{\lambda_1^f} \xi \tilde{\xi} z^{f,\frac{1}{1-\xi}} (1-\mu), \tag{C.10}$$

$$\chi(1+\eta)(N_2^h)^\eta = \frac{\lambda_2^h}{\lambda_1^h} \xi \tilde{\xi} z^{h,\frac{1}{1-\xi}} + e_1 \chi^a b_2 \exp^{\{b_1 N_{h,2}^f - b_2 N_2^h\}}. \tag{C.11}$$

Fiscal Balance. We assume that in each country, the government finances the cost subsidy on intermediate goods production by levying lump-sum taxes, and it always runs a balanced budget. The governments' budget constraints in the home and foreign countries are, respectively,

$$T_2^h = \tau N_2^h x_2^{h*}, \tag{C.12}$$

$$T_2^f = \tau N_2^f x_2^{f*} + \tau N_{h,2}^f x_{h,2}^{f*} \frac{1}{e_2}. \tag{C.13}$$

Households. The households receive wage income from the final good production, profit income from intermediate firms, and make consumption after paying tax bills. We assume that the financial market is complete and households in the two countries can trade a short-term financial asset to smooth consumption across periods. The households in each country maximize their lifetime utilities,

$$U^h(z^h, z^f) = \max_{c_1^h, c_2^h, B^h} \left\{ u(c_1^h) + u(c_2^h) \right\},$$

$$\text{s.t.} \quad c_2^h + B^h(1 + r^h) = w_2^h - T_2^h + \Pi_2^{HI}, \tag{C.14}$$

$$c_1^h + F_h(N_2^h) = y_1^h + B^h, \tag{C.15}$$

$$U^f(z^h, z^f) = \max_{c_1^f, c_2^f, B^f} \left\{ u(c_1^f) + u(c_2^f) \right\},$$

$$\text{s.t.} \quad c_2^f = w_2^f - T_2^f + \Pi_2^{FI} + \Pi_2^{FA} + B^f(1 + r^h)\frac{1}{e_2}, \tag{C.16}$$

$$c_1^f + F_f(N_2^f) + F_{hf}(N_{h,2}^f, N_2^h) + B^f \frac{1}{e_1} = y_1^f, \tag{C.17}$$

where B^h and B^f denote short-term bonds denominated in home currencies. $B^h > 0$ and $B^f > 0$ indicate that country-H (country-F) is a borrower (saver) in the first period. The households' bond Euler equations are

$$1 = \frac{\lambda_2^h}{\lambda_1^h}(1 + r^h), \qquad 1 = \frac{\lambda_2^f}{\lambda_1^f}(1 + r^h)\frac{e_1}{e_2}. \tag{C.18}$$

Consumption Good Importers. We assume there is no cost of shipping consumption good across the border in the first period. In the second period, there is a continuum of final good importers shipping the final products X_2 from the foreign to the home economy. Transportation of goods are associated with a shipping cost that is proportional to trade volume: $1 - \frac{\kappa}{2}X_2$. Since importers are competitive, we have $-X_2 e_2 + X_2\left(1 - \frac{\kappa}{2}X_2\right) = 0$. Zero-profit condition implies that

$$e_2 = 1 - \frac{\kappa}{2}X_2. \tag{C.19}$$

Aggregation. Taking equations (C.1), (C.3), (C.12), (C.13) into the households' second-period budget constraints (C.14) and (C.16) gives us the following

$$c_2^h + B^h(1+r^h) = N_2^h\left(\xi^{\frac{\xi}{1-\xi}} - \xi^{\frac{1}{1-\xi}}\right) z^{h,\frac{1}{1-\xi}}, \tag{C.20}$$

$$c_2^f = B^f(1+r^h)\frac{1}{e_2} + \left(\mu N_2^f + (1-\mu)N_{h,2}^f e_2^{\frac{\xi}{1-\xi}}\right)\left(\xi^{\frac{\xi}{1-\xi}} - \xi^{\frac{1}{1-\xi}}\right) z^{f,\frac{1}{1-\xi}}. \tag{C.21}$$

In equilibrium, the balance-of-payment condition holds,

$$\text{Capital outflows in country-H:} \quad B^h(1+r^h) = N_{h,2}^f x_{h,2}^{f*} - X_2 e_2. \tag{C.22}$$

$$\text{Capital inflows in country-F:} \quad B^f(1+r^h)\frac{1}{e_2} = N_{h,2}^f x_{h,2}^{f*}\frac{1}{e_2} - X_2. \tag{C.23}$$

Also, the bond market clears,

$$B^h = B^f. \tag{C.24}$$

Bringing equations (C.22), (C.23), (C.24) into (C.15), (C.17), (C.20), (C.21), we have the resource constraints as follows,

$$c_2^h + N_{h,2}^f x_{h,2}^{f*} - X_2 e_2 = y_2^h - N_2^h x_2^{h*}, \tag{C.25}$$

$$c_2^f + X_2 = y_2^f - N_2^f x_2^{f*}, \tag{C.26}$$

$$c_1^h + e_1 c_1^f + F_h(N_2^h) + e_1 F_f(N_2^f) + e_1 F_{hf}(N_{h,2}^f) = y_1^h + e_1 y_1^f. \tag{C.27}$$

Lastly, equation (C.18) implies the Backus-Smith condition,

$$\frac{e_2}{e_1}\frac{\lambda_2^h}{\lambda_1^h} = \frac{\lambda_2^f}{\lambda_1^f}. \tag{C.28}$$

Our model still leaves the first-period exchange rate e_1 indeterminate. To close the model, we put weight on the utility function such that $e_1 = \lambda_1^f / \lambda_1^h = 1$. In this case, we eliminate the effect of country size. Then, the risk-sharing condition becomes $e_2 = \lambda_2^f / \lambda_2^h$.

Equivalence. The *competitive equilibrium* consists of the allocations $\{c_1^h, c_1^f, N_2^h, N_2^f, N_{h,2}^f, c_2^h, c_2^f, X_2, x_2^h, x_2^f, x_{h,2}^f\}$ and prices $\{r^h, r^f, e_2\}$ such that i) Households in each country maximizes their lifetime utilities; ii) innovators and adopters make investment decisions; iii) intermediate good firms maximize profits; iv) final good packagers combine intermediate goods and labor to produce outputs; v) consumption good importers' zero-profit condition holds; vi) bond and good markets clear.

The solution to the competitive equilibrium is characterized by equations (C.2), (C.9), (C.10), (C.11), (C.18), (C.19), (C.25), (C.26), (C.27), (C.28), which are exactly the same as the optimality conditions in the social planner's problem.

A.2 Adoption in Both Countries

This section extends to baseline environment to include adoption sector in both home and foreign countries. We will show that the same mechanism works if the adoption sector in the home country is smaller than the foreign country. In the following, we only introduce the model part that is different from the baseline setup. The production functions in the home and foreign countries are

$$y_2^h = z^h \left(\mu^{h,1-\xi} \sum_{i=1}^{N_2^h} x_{2,i}^{h,\xi} + (1-\mu^h)^{1-\xi} \sum_{j=1}^{N_{f,2}^h} x_{f,2,j}^{h,\xi} \right), \tag{C.29}$$

$$y_2^f = z^f \left(\mu^{f,1-\xi} \sum_{i=1}^{N_2^f} x_{2,i}^{f,\xi} + (1-\mu^f)^{1-\xi} \sum_{j=1}^{N_{h,2}^f} x_{h,2,j}^{f,\xi} \right). \tag{C.30}$$

where μ^h and μ^f are respectively the innovation sector in the home and foreign countries. The optimal level of intermediate goods are

$$x_2^{h*} = \xi^{\frac{1}{1-\xi}} z^{h,\frac{1}{1-\xi}} \mu^h, \qquad x_{h,2}^{f*} = \xi^{\frac{1}{1-\xi}} z^{f,\frac{1}{1-\xi}} e_2^{\frac{1}{1-\xi}} (1-\mu^f), \tag{C.31}$$

$$x_2^{f*} = \xi^{\frac{1}{1-\xi}} z^{f,\frac{1}{1-\xi}} \mu^f, \qquad x_{f,2}^{h*} = \xi^{\frac{1}{1-\xi}} z^{h,\frac{1}{1-\xi}} e_2^{-\frac{1}{1-\xi}} (1-\mu^h). \tag{C.32}$$

Taking the intermediate inputs into the production functions give us the following,

$$y_2^h = z^h \xi^{\frac{\xi}{1-\xi}} \left[\mu^h N_2^h + (1-\mu^h) N_{f,2}^h e_2^{-\frac{\xi}{1-\xi}} \right], \tag{C.33}$$

$$y_2^f = z^f \xi^{\frac{\xi}{1-\xi}} \left[\mu^f N_2^f + (1-\mu^f) N_{h,2}^f e_2^{\frac{\xi}{1-\xi}} \right]. \tag{C.34}$$

The resource constraints of the economy are given by

$$y_2^h = c_2^h + N_2^h x_2^{h*} + N_{h,2}^f x_{h,2}^{f*}, \tag{C.35}$$

$$y_2^f = c_2^f + N_2^f x_2^{f*} + N_{f,2}^h x_{f,2}^{h*}, \tag{C.36}$$

$$y_1^f + y_1^d = c_1^f + c_1^d + F_h(N_2^h) + F_f(N_2^f) + F_{hf}(N_{h,2}^f) + F_{fh}(N_{f,2}^h). \tag{C.37}$$

where the cost functions of innovation (adoption) are the same as before:

$$F_h(N_2^h) = \chi (N_2^h)^{1+\eta}, \qquad F_{h,f}(N_{h,2}^f, N_2^h) = \chi^a \exp^{\{b_1 N_{h,2}^f - b_2 N_2^h\}},$$

$$F_f(N_2^f) = \bar{\chi} (N_2^h)^{1+\eta}, \qquad F_{f,h}(N_{f,2}^h, N_2^f) = \bar{\chi}^a \exp^{\{b_1 N_{f,2}^h - b_2 N_2^f\}}.$$

The same as before, the social planner's problem is to choose N_2^h, N_2^f, $N_{f,2}^h$, $N_{h,2}^f$ that maximizes the lifetime utility (equation 22 in the paper) subject to (C.35), (C.36), (C.37). For tractability of the model and make this extension comparable to the baseline setup, we assume that the trade is balanced between the two countries: $N_{h,2}^f x_{h,2}^{f*} = N_{f,2}^h x_{f,2}^{h*}$. As a result, the resource constraints in the second period can be reformulated into the following

$$c_2^h = z^h \tilde{\xi} \left[\mu^h N_2^h + (1-\mu^h) N_{f,2}^h e_2^{-\frac{\xi}{1-\xi}} \right], \tag{C.38}$$

$$c_2^f = z^f \tilde{\xi} \left[\mu^f N_2^f + (1-\mu^f) N_{h,2}^f e_2^{\frac{\xi}{1-\xi}} \right], \tag{C.39}$$

where $\tilde{\xi} = \xi^{\frac{\xi}{1-\xi}} - \xi^{\frac{1}{1-\xi}}$. The optimal investment decisions are characterized by

$$(1+\eta)\chi(N_2^h)^\eta = \mathcal{M}_2^h \tilde{\xi} \mu^h z^{h,\frac{1}{1-\xi}} + \mathcal{M}_2^f \frac{b_2}{b_1}(1-\mu^f)\tilde{\xi} z^{f,\frac{1}{1-\xi}} e_2^{\frac{\xi}{1-\xi}}, \tag{C.40}$$

$$(1+\eta)\bar{\chi}(N_2^f)^\eta = \mathcal{M}_2^f \tilde{\xi} \mu^f z^{f,\frac{1}{1-\xi}} + \mathcal{M}_2^h \frac{b_2}{b_1}(1-\mu^h)\tilde{\xi} z^{h,\frac{1}{1-\xi}} e_2^{-\frac{\xi}{1-\xi}}, \tag{C.41}$$

$$\chi^a b_1 \exp^{\{b_1 N_{h,2}^f - b_2 N_2^h\}} = \mathcal{M}_2^f (1-\mu^f)\tilde{\xi} z^{f,\frac{1}{1-\xi}} e_2^{\frac{\xi}{1-\xi}}, \tag{C.42}$$

$$\bar{\chi}^a b_1 \exp^{\{b_1 N_{f,2}^h - b_2 N_2^f\}} = \mathcal{M}_2^h (1-\mu^h)\tilde{\xi} z^{h,\frac{1}{1-\xi}} e_2^{-\frac{\xi}{1-\xi}}. \tag{C.43}$$

The first-period exchange rate: $e_1 = 1$. The exchange rate in the second period is determined by

$$e_2 = \frac{\lambda_2^f}{\lambda_2^h}. \tag{C.44}$$

Analytical Solutions. To derive analytical solutions, we still make the assumption that firms are risk neutral. Then, we derive log-linearized solutions around a deterministic steady state. First, we write the number of patents as a function of shocks and exchange rate:

$$\hat{N}_2^h = A_{hh}\hat{z}^h + A_{hf}\hat{z}^f + A_{he}\hat{e}_2, \tag{C.45}$$

$$\hat{N}_2^f = A_{ff}\hat{z}^f + A_{fh}\hat{z}^h - A_{fe}\hat{e}_2, \tag{C.46}$$

$$\hat{N}_{h,2}^f = \frac{b_2}{b_1}A_{hh}\hat{z}^h + \left(\frac{b_2}{b_1}A_{hf} + \frac{1}{b_1}\frac{1}{1-\xi}\right)\hat{z}^f + \left(\frac{b_2}{b_1}A_{he} + \frac{1}{b_1}\frac{\xi}{1-\xi}\right)\hat{e}_2, \tag{C.47}$$

$$\hat{N}_{f,2}^h = \frac{b_2}{b_1}A_{ff}\hat{z}^f + \left(\frac{b_2}{b_1}A_{fh} + \frac{1}{b_1}\frac{1}{1-\xi}\right)\hat{z}^h - \left(\frac{b_2}{b_1}A_{fe} + \frac{1}{b_1}\frac{\xi}{1-\xi}\right)\hat{e}_2. \tag{C.48}$$

where the coefficients are

$$A_{hh} = \frac{\frac{1}{1-\xi}\frac{1}{\eta}\mu^h}{\mu^h + \frac{b_2}{b_1}(1-\mu^f)}, \quad A_{hf} = \frac{\frac{1}{1-\xi}\frac{1}{\eta}\frac{b_2}{b_1}(1-\mu^f)}{\mu^h + \frac{b_2}{b_1}(1-\mu^f)}, \quad A_{he} = \frac{\frac{\xi}{1-\xi}\frac{1}{\eta}\frac{b_2}{b_1}(1-\mu^f)}{\mu^h + \frac{b_2}{b_1}(1-\mu^f)},$$
$$A_{ff} = \frac{\frac{1}{1-\xi}\frac{1}{\eta}\mu^f}{\mu^f + \frac{b_2}{b_1}(1-\mu^h)}, \quad A_{fh} = \frac{\frac{1}{1-\xi}\frac{1}{\eta}\frac{b_2}{b_1}(1-\mu^h)}{\mu^f + \frac{b_2}{b_1}(1-\mu^h)}, \quad A_{fe} = \frac{\frac{\xi}{1-\xi}\frac{1}{\eta}\frac{b_2}{b_1}(1-\mu^h)}{\mu^f + \frac{b_2}{b_1}(1-\mu^h)}.$$

Taking these equations into the linearized version of resource constraints (C.38)-(C.39) and using the risk-sharing condition (C.44) gives us the following expressions of exchange rate,

$$\hat{e}_2 = \frac{\overbrace{\left[A_{hh}\left(\mu^h - (1-\mu^f)\frac{b_2}{b_1}\right) - A_{fh}\left(\mu^f - (1-\mu^h)\frac{b_2}{b_1}\right) + \frac{1}{1-\xi}\left(1 + \frac{1}{b_1}(1-\mu^h)\right)\right]}^{E>0}\hat{z}^h + \overbrace{\left[A_{hf}\left(\mu^h - (1-\mu^f)\frac{b_2}{b_1}\right) - A_{ff}\left(\mu^f - (1-\mu^h)\frac{b_2}{b_1}\right) - \frac{1}{1-\xi}\left(1 + \frac{1}{b_1}(1-\mu^f)\right)\right]}^{F<0}\hat{z}^f}{\underbrace{\frac{1}{\sigma} - A_{he}\left(\mu^h - (1-\mu^f)\frac{b_2}{b_1}\right) - A_{fe}\left(\mu^f - (1-\mu^h)\frac{b_2}{b_1}\right) + \frac{\xi}{1-\xi}\left(1 + \frac{1}{b_1}\right)(2 - \mu^h - \mu^f)}_{D>0}} \tag{C.49}$$

The home and foreign consumption functions are

$$\begin{aligned} \hat{c}_2^h = & \overbrace{\left\{\frac{1}{1-\xi} + \mu^h A_{hh} + (1-\mu^h)\left(\frac{b_2}{b_1}A_{fh} + \frac{1}{b_1}\frac{1}{1-\xi}\right) + \left[\mu^h A_{he} - (1-\mu^h)\left(\frac{b_2}{b_1}A_{fe} + \frac{\xi}{1-\xi}\left(\frac{1}{b_1}+1\right)\right)\right]\frac{E}{D}\right\}}^{\tilde{C}_1^D} \times \hat{z}^h \\ & + \underbrace{\left\{\mu^h A_{hf} + (1-\mu^h)A_{ff}\frac{b_2}{b_1} + \left[\mu^h A_{he} - (1-\mu^h)\left(\frac{b_2}{b_1}A_{fe} + \frac{\xi}{1-\xi}\left(\frac{1}{b_1}+1\right)\right)\right]\frac{F}{D}\right\}}_{\tilde{C}_2^D} \times \hat{z}^f, \end{aligned} \tag{C.50}$$

$$\begin{aligned} \hat{c}_2^h = & \overbrace{\left\{\mu^f A_{fh} + (1-\mu^f)A_{hh}\frac{b_2}{b_1} + \left[-\mu^f A_{fe} + (1-\mu^f)\left(\frac{b_2}{b_1}A_{he} + \frac{\xi}{1-\xi}\left(\frac{1}{b_1}+1\right)\right)\right]\frac{E}{D}\right\}}^{\tilde{C}_1^F} \times \hat{z}^h \\ & + \underbrace{\left\{\frac{1}{1-\xi} + \mu^f A_{ff} + (1-\mu^f)\left(\frac{b_2}{b_1}A_{hf} + \frac{1}{b_1}\frac{1}{1-\xi}\right) + \left[-\mu^f A_{fe} + (1-\mu^f)\left(\frac{b_2}{b_1}A_{he} + \frac{\xi}{1-\xi}\left(\frac{1}{b_1}+1\right)\right)\right]\frac{F}{D}\right\}}_{\tilde{C}_2^F} \times \hat{z}^f. \end{aligned} \tag{C.51}$$

Given the above solutions, we have the following lemma to characterize the exchange rate fluctuations under productivity shocks. Similar to the analysis before, we decompose the productivity shocks to a common component $\hat{z}$ and a mean-preserving part $\hat{\epsilon}$.

Lemma 3. *Under the following conditions:*

(i) $\frac{1}{\sigma} + \frac{\xi}{1-\xi}\left(1 + \frac{1}{b_1}\right)(2 - \mu^h - \mu^f) > A_{de}\left(\mu^h - (1-\mu^f)\frac{b_2}{b_1}\right) + A_{fe}\left(\mu^f - (1-\mu^h)\frac{b_2}{b_1}\right)$ *;*

(ii) $\frac{1}{\eta}\left(1 - \frac{b_2}{b_1}\right) > \frac{1}{b_1}$ *.*

We argue that the real exchange rate positively comoves with the common productivity shock $\frac{\partial \hat{e}_2}{\partial \hat{z}} > 0$ *if and only if* $\mu^h > \mu^f$*. In addition, the real exchange rate depreciates when there is a positive mean-preserving productivity shock; that is,* $\frac{\partial \hat{e}_2}{\partial \hat{\epsilon}} > 0$*.*

Proof. **The first half:** Similar to the proof of Lemma 1, condition (i) is equivalent to that $D > 0$. Taking the expression of coefficients "A_{ij}, $i, j = h, f$" into equation (C.49), we have

$$E + F = \frac{1}{\eta}\left(1 - \frac{b_2}{b_1}\right)(\mu^h - \mu^f) - \frac{1}{b_1}(\mu^h - \mu^f)$$

As a result, under condition (ii), we have that $E + F > 0$ if and only if $\mu^h - \mu^f > 0$. It indicates that the real exchange rate positively comoves with the common productivity shock if and only if the innovation sector in the home country is larger than the foreign country.

The second half: Based on the expressions of E and F in equation (C.49), we have

$$E - F = \frac{1}{1-\xi}\left(2 + \frac{1}{b_1}(2 - \mu^h - \mu^f)\right) + \frac{\frac{1}{1-\xi}\frac{1}{\eta}\left(\mu^h - \frac{b_2}{b_1}(1-\mu^f)\right)^2}{\mu^h + \frac{b_2}{b_1}(1-\mu^f)} + \frac{\frac{1}{1-\xi}\frac{1}{\eta}\left(\mu^f - \frac{b_2}{b_1}(1-\mu^h)\right)^2}{\mu^f + \frac{b_2}{b_1}(1-\mu^h)} > 0$$

always holds. It indicates that the exchange rate always depreciates when there is a mean-preserving shock that makes the home productivity higher than the foreign economy. □

The following lemma indicates that the home country has more volatile consumption fluctuation than the foreign country if its innovation sector is larger.

Lemma 4. *Under the conditions (i) and (ii) in Lemma 3, country-H's consumption is more sensitive to the common productivity shock than that in country-F,* $\frac{\partial \hat{c}_2^h}{\partial \hat{z}} > \frac{\partial \hat{c}_2^f}{\partial \hat{z}}$*, if and only if* $\mu^h > \mu^f$*. In addition, a positive mean-preserving productivity shock increases global outputs,* $\frac{\partial \hat{y}_2}{\partial \hat{\epsilon}} > 0$*, if and only if* $\mu^h > \mu^f$*.*

Proof. **The first half:** The home consumption is more sensitive to $\hat{z}$ shock whenever the following condition holds

$$\tilde{C}_1^D + \tilde{C}_2^D > \tilde{C}_1^F + \tilde{C}_2^F.$$

Using the expression of coefficients in equations (C.50)-(C.51), that is equivalent to prove

$$\frac{1}{1-\xi}\frac{1}{\eta}\left(1-\frac{b_2}{b_1}\right)(\mu^d-\mu^f)-(\mu^d-\mu^f)\frac{1}{1-\xi}\frac{1}{b_1}+$$
$$\left[A_{he}\left(\mu^h-\frac{b_2}{b_1}(1-\mu^f)\right)+A_{fe}\left(\mu^f-\frac{b_2}{b_1}(1-\mu^h)\right)-(2-\mu^h-\mu^f)\frac{\xi}{1-\xi}\left(\frac{1}{b_1}+1\right)\right]\frac{E+F}{D}>0.$$

Given conditions (i)-(ii) and the implied relationships $E+F>0$ and $D>0$, the above inequality holds if and only if $\mu^h>\mu^f$. The result indicates that when there is positive shock to global productivity, the home consumption increases by more than foreign consumption whenever the home innovation sector is larger than the foreign country's.

The second half: The mean-preserving shock expands the global production whenever the following condition holds

$$\tilde{C}_1^D-\tilde{C}_2^D>\tilde{C}_2^F-\tilde{C}_1^F.$$

The condition is equivalent to the following,

$$-\frac{1}{1-\xi}\frac{1}{b_1}(\mu^d-\mu^f)+\frac{1}{1-\xi}\frac{1}{\eta}\left(\mu^h-\frac{b_2}{b_1}(1-\mu^f)\right)-\frac{1}{1-\xi}\frac{1}{\eta}\left(\mu^f-\frac{b_2}{b_1}(1-\mu^h)\right)+$$
$$\left[\frac{\xi}{1-\xi}\frac{1}{\eta}\frac{b_2}{b_1}(\mu^d-\mu^f)+(\mu^d-\mu^f)\frac{\xi}{1+\xi}\left(1+\frac{1}{b_1}\right)\right]\frac{E-F}{D}>0.$$

Under conditions (i)-(ii) and $E+F>0$, $E-F>0$, and $D>0$, the relationship always holds whenever $\mu^h>\mu^f$. That is to say, a mean-preserving shock increases the overall world production if the home country's innovation sector is larger than the foreign country. □

Denote m_2^h and m_2^f as the log SDF in the home and foreign countries. Lemmas 3 and 4 together imply the following properties of the currency risk premium.

Proposition 3. *Suppose that the conditions (i) and (ii) in Lemma 3 hold, and we assume the following condition (iii) holds:*

$$-\frac{1}{1-\xi}\left(1+(1-\mu^f)\frac{1}{b_1}\right)-\mu^f(A_{ff}-A_{fh})+(1-\mu^f)\frac{b_2}{b_1}(A_{hh}-A_{hf})$$
$$<\mu^f A_{fe}-(1-\mu^f)\left[\frac{b_2}{b_1}A_{he}+\frac{\xi}{1-\xi}\left(1+\frac{1}{b_1}\right)\right]<$$
$$\frac{1}{1-\xi}\left(1+(1-\mu^f)\frac{1}{b_1}\right)+\left(\mu^f+(1-\mu^f)\frac{b_2}{b_1}\right)\frac{1}{1-\xi}\frac{1}{\eta}$$

Then the currency risk premium for going long in F and short in H is positive,

$$\mathbb{E}\left[rx_2\right] = r^f - r^h + \mathbb{E}\left[\Delta \log e_2\right] = \frac{1}{2} var(m_2^h) - \frac{1}{2} var(m_2^f) > 0, \tag{C.52}$$

$$\log(\mathbb{E}\left[RX_2\right]) = -cov(m_2^h, \Delta \log e_2) > 0. \tag{C.53}$$

whenever the innovation sector is larger in the home country than in the foreign country: $\mu^h > \mu^f$. *In addition, under the same conditions, the carry trade return is procyclical:* $cov(\hat{y}_2, rx_2) = cov(\hat{y}_2, \log e_2) > 0$.

Proof. Using the expression of currency excess returns in proposition 1, we only need to prove that $\text{var}(m_2^h) > \text{var}(m_2^f)$. Since we have CRRA utility function, that is equivalent to proving $\text{var}(\hat{c}_2^h) > \text{var}(\hat{c}_2^f)$. Using the notation above, that only requires us to prove the following,

$$\tilde{C}_1^D + \tilde{C}_2^D > \tilde{C}_1^F + \tilde{C}_2^F > 0,$$

$$\tilde{C}_1^D - \tilde{C}_2^D > \tilde{C}_2^F - \tilde{C}_1^F > 0.$$

The condition (iii) shows that $\tilde{C}_1^F + \tilde{C}_2^F > 0$ and $\tilde{C}_2^F - \tilde{C}_1^F > 0$. In the end, we have that the home country is more exposed to global productivity shocks than the foreign country, thus having a higher volatility. The high volatility country should have a lower risk premium due to the precautionary saving motive. The risk premium in level must be positive because $\log(\mathbb{E}\left[RX_2\right]) = \frac{1}{2}\text{var}(m_2^h) - \frac{1}{2}\text{var}(m_2^f) + \frac{1}{2}\text{var}(\hat{e}_2) > 0$. □

The following proposition describes the correlation of SDF and the cyclicality of intermediate trade.

Proposition 4. *We suppose that conditions (i)-(iii) hold and also assume that* $\mu^h > \mu^f$. *Then the correlation of countries' SDFs is higher than the correlation of their productivity shocks; that is,*

$$corr(m_2^h, m_2^f) = corr(\hat{c}_2^h, \hat{c}_2^f) > corr(z^h, z^f). \tag{C.54}$$

Moreover, the net export of intermediate goods from H to F is procyclical, $cov(\hat{y}_2, \widehat{EX}_{h,2}^f - \widehat{EX}_{f,2}^h) >$

0, *whenever the following condition (iv) holds,*

$$\frac{b_2}{b_1}(A_{hh}+A_{ff})+\left(\frac{b_2}{b_1}(A_{he}-A_{fe})+\frac{1}{b_1}\frac{2(1+\xi)}{1-\xi}\right)\frac{E-F}{D}>\frac{b_2}{b_1}(A_{hf}+A_{fh})+\frac{2}{1-\xi}\left(\frac{1}{b_1}+1\right).$$

Proof. Under conditions (i)-(iii) and $\mu^h > \mu^f$, we have the following,

$$|\tilde{C}_1^D+\tilde{C}_2^D|>|\tilde{C}_1^F+\tilde{C}_2^F|,$$
$$|\tilde{C}_1^D-\tilde{C}_2^D|>|\tilde{C}_2^F-\tilde{C}_1^F|.$$

Let $\bar{\rho}=\frac{\sigma^{\epsilon,2}}{\sigma^{z,2}}$, then we have the following

$$\text{corr}(\hat{c}_2^h,\hat{c}_2^f)=\frac{1-\frac{(\tilde{C}_1^D-\tilde{C}_2^D)(\tilde{C}_2^F-\tilde{C}_1^F)}{(\tilde{C}_1^D+\tilde{C}_2^D)(\tilde{C}_2^F+\tilde{C}_1^F)}\bar{\rho}}{\left[1+\left(\frac{\tilde{C}_1^D-\tilde{C}_2^D}{\tilde{C}_1^D+\tilde{C}_2^D}\right)^2\bar{\rho}\right]^{\frac{1}{2}}\left[1+\left(\frac{\tilde{C}_2^F-\tilde{C}_1^F}{\tilde{C}_2^F+\tilde{C}_1^F}\right)^2\bar{\rho}\right]^{\frac{1}{2}}}>\frac{1-\bar{\rho}}{1+\bar{\rho}}=\text{corr}(\hat{z}^h,\hat{z}^f),$$

for each $\bar{\rho}\in[0,\infty)$. So, the correlation of SDF is always higher than the correlation of shocks.

The bilateral export between two countries can be written as

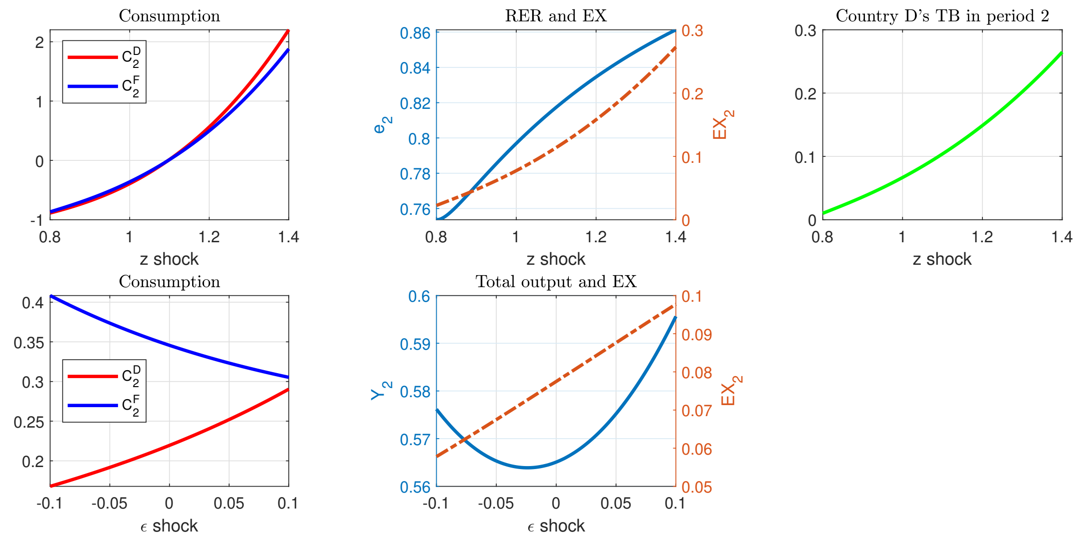
$$\hat{EX}_{h,2}^f=\frac{b_2}{b_1}A_{hh}\hat{z}^h+\left(\frac{b_2}{b_1}A_{hf}+\left(\frac{1}{b_1}+1\right)\frac{1}{1-\xi}\right)\hat{z}^f+\left(\frac{b_2}{b_1}A_{he}+\frac{1}{b_1}\frac{\xi}{1-\xi}+\frac{1}{1-\xi}\right)\hat{e}_2,$$
$$\hat{EX}_{f,2}^h=\frac{b_2}{b_1}A_{ff}\hat{z}^f+\left(\frac{b_2}{b_1}A_{fh}+\left(\frac{1}{b_1}+1\right)\frac{1}{1-\xi}\right)\hat{z}^h-\left(\frac{b_2}{b_1}A_{fe}+\frac{1}{b_1}\frac{\xi}{1-\xi}+\frac{1}{1-\xi}\right)\hat{e}_2$$

When there is only a common productivity shock $\hat{z}^h=\hat{z}^f=\hat{z}$, it is easy to see that $\hat{EX}_{h,2}^f-\hat{EX}_{f,2}^h$ is increasing in $\hat{z}$. When there is only a mean-preserving shock $\hat{z}^h=\hat{z}^f=\hat{\epsilon}$, the net export $\hat{EX}_{h,2}^f-\hat{EX}_{f,2}^h$ is increasing in $\hat{\epsilon}$ if and only if the condition (iv) holds. In sum, we proved that conditions (i)-(iv) are sufficient to ensure that net export positively correlates with output and exchange rate. □

A.3 Risk-Averse Firms

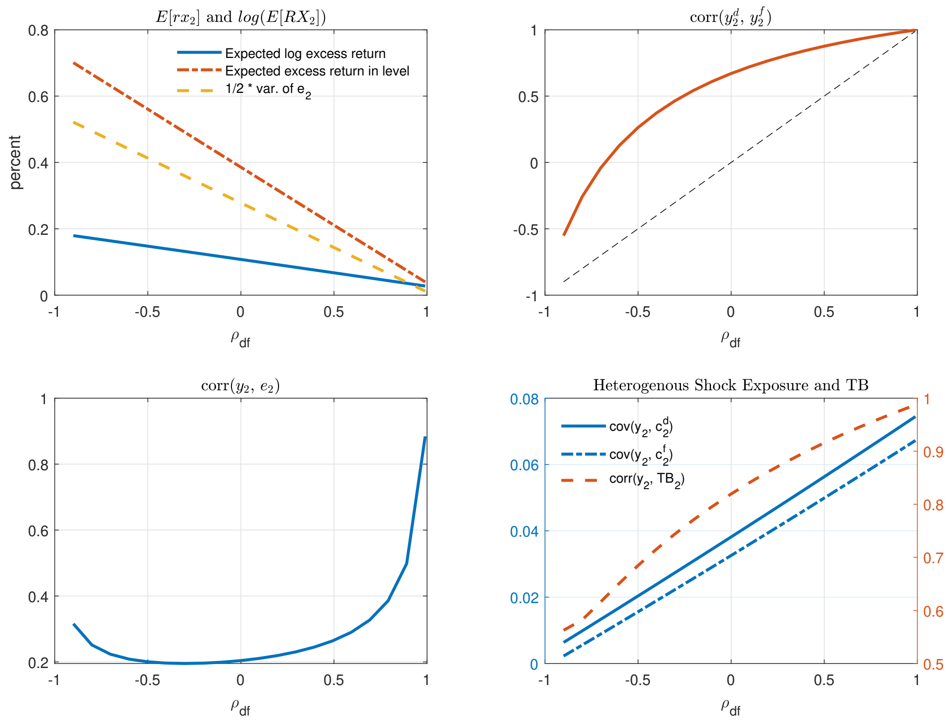
In the baseline environment, we derive analytical results based on the assumption that innovating firms are risk-neutral and trade is balanced. In this section, we use a numerical example to show that the mechanism still works if we close the model by dropping these assumptions. Figure C.21 shows the state-dependent consumption, output, exchange rate, and trade balance in the two-period model. Figure C.22 shows the predicted risk premium and other business cycle moments.

Figure C.21: Risk-Averse Firms: Consumption Risk Sharing



Note: This picture shows the consumption comovement, exchange rate, and aggregate production in the two-period model with risk-averse firms and unbalanced trade. The parameter values are: $\sigma = 0.5$, $\mu = 0.5$, $\xi = 0.45$, $\eta = 0.35$, $b_1 = 2$, $b_2 = 0.3$, $\kappa = 30$. In the upper panel, we assume productivities perfectly comove between two countries; that is $\hat{z}^h = \hat{z}^f = \hat{z}$. In the lower panel, we assume a mean-preserving shock that enlarges the difference in productivity between the two countries; that is, $\hat{z}^h = -\hat{z}^f = \hat{\epsilon}$. Trade balance in country-H is given by $TB_2 = EX_2 - X_2 e_2$.

Figure C.22: Risk-Averse Firms: Predicted Model Moments for Different Shock Correlations (ρ_{df})



Note: This picture displays theoretical moments for the model with risk-averse firms and unbalanced trade. The parameter values are $\sigma = 0.5$, $\mu = 0.5$, $\xi = 0.45$, $\eta = 0.35$, $b_1 = 2$, $b_2 = 0.3$, $\kappa = 30$. Trade balance in country-H is given by $TB_2 = EX_2 - X_2 e_2$.