Technology Diffusion and Currency Risk Premia

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Abstract

This paper identifies a unique dimension of currency carry trade related to the intensity of technology spillover across countries. In the data, technology diffusion is measured by the R&D ingredient embodied in manufactured goods imports. Empirical evidence shows that the difference in the tech-diffusion explains the cross-sectional variation of currency excess returns. Specifically, countries adopting more technologies tend to have higher interest rates and excess returns. We rationalize this observation by building a simple two-country model with technology innovation and adoption. The adoption sector insulates tech-diffusion countries from global productivity shocks, resulting in a lower productivity risk exposure. As a result, investors require a risk premium for holding the high-interest-rate currency as compensation for its procyclical returns.

Keywords: Exchange Rate; Currency Risk Premium, Carry Trade Portfolio, Cross-Country Technology Transmission, Technology Adoption.

JEL Classification: F31; G12; G15; O33

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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 premium. Then, we rationalize this finding with a simple two-country model 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, etc.), primarily associated with a time-varying risk premium charged by investors in the FX market. Abundant empirical studies (e.g., Hassan and Mano, 2019; Lustig et al., 2011a; Lustig and Verdelhan, 2007, etc.) shows that a naive strategy that involves a long position in high-interest-rate currencies and short position in low-interest-rate currencies (i.e., the carry strategy) generate prominent excess returns.

Using the 6-digit level of UN Comtrade data, we find that the prevalent currency risk premia across countries can be attributed to their different abilities in adopting foreign R&D in the intensive margin of trade. Technology diffusion, a dynamic consequence of adoption, is a key dimension of the carry trade strategy. Why does the difference in the degree of tech diffusion imply different productivity and consumption risk exposure in the global business cycle? And how does this structure of risk exposure contribute to the persistent currency risk premium in the long run?

We develop a measure of technology diffusion using the knowledge concentration in the global trade environment. The factor captures the intensity of R&D incorporated in the import quantities of each manufacturing good. Intuitively, a high tech-diffusion measure implies that the country is central to the global R&D flow, while the low value 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 as they receive more values of R&D goods from their trade partners. On the other hand, low-interest-rate countries make R&D on 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. Particularly, Japan and Switzerland, considered typical funding currencies in the FX market, actively

[1] A closely related paper is Gavazzoni and Santacreu (2020) who use a quantitative model to show that the international technology transmission through adoption can account for the cross-country propagation of risk and asset price anomaly. They also provide empirical evidence that the R&D content of trade is positively correlated with the stock market return comovement and negatively correlated with the volatility of exchange rates.

[2] The group is called "G10 Currencies" and it is considered the most traded and liquid currency 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.

spend R&D efforts. In contrast, New Zealand and Australia, well-known for their high forward discounts and considered investment currencies, are reluctant to innovate. Moreover, the direction of currency excess return is generally aligned with the forward discount, indicating the profitability of the carry trade strategy and the violation of UIP. This finding invites us to consider the fundamental link between international knowledge diffusion and the carry trade strategy.

We start with a cross-sectional regression of future currency excess returns on our tech-diffusion measure while controlling for the country size, inflation, and trade openness. In line with our conjecture, we find that tech-diffusion is a strong positive predictor of the cross-section of currency returns and interest rate difference. The predicting power still exists after we control for countries' GDP share à la Hassan (2013), which is considered as the key explaining factor for the carry trade returns across developed economies. To further assess the role of tech-diffusion in explaining cross-sectional return difference, we construct a common risk factor. Specifically, we consider a zero-cost investment strategy that goes long in currencies of high-diffusion countries (i.e., adopters) and shorts the low-tech-diffusion economies (i.e., innovators). Over the sample period from 1993 to 2019, the strategy offers an annualized return of 2.82% for OECD countries and 3.50% for the G10 currencies with a Sharpe ratio of 42% and 43%. Over the same period, a monthly-rebalancing carry trade strategy exhibits similar dynamics, achieving an average return of 5.00% for OECD countries and 4.70% for G10 currencies before transaction costs.

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. The results show that the tech-diffusion factor is priced in the cross-section of currency excess returns, and it can capture most of the carry trade variability. We also show that the portfolios sorted on tech-diffusion betas lead to the same monotone pattern of excess returns or interest rates. In particular, 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.

Recently, Ready et al. (2017) and Richmond (2019) also build trade-related factors and demonstrate their success in explaining the cross-section of the currency risk premium. Specifically, Ready et al. (2017) shows that countries' relative advantage 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 import ratio to capture the extent to which a country specializes in the production of basic commodities. Meanwhile, Richmond (2019) build an empirical centrality measure that echos the 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 the global consumption growth. Although our tech-diffusion is also a trade-related factor in predicting the cross-section of currency returns, it conveys different information.[3] The tech diffusion reflects the R&D content of import flows in the intensive margin of trade. The high-interest-rate countries usually adopt new technologies, while low-interest-rate countries design them.

We show that countries' relative rankings based on our measure and alternative measures in the literature do not perfectly coincide. 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 tech-diffusion and centrality is even looser than the connection between tech-diffusion and 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 tech-diffusion 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 factor still has strong predicting power for the cross-sectional currency 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 the 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

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

stronger predicting power for the unconditional currency risk premium. This is not surprising given that our tech-diffusion measure captures countries' heterogeneous risk exposure, which is an unconditional property in its nature. Also, to guard against the possibility of a "lucky" factor of Harvey and Liu (2021) and Lewellen et al. (2010), we show that our empirical results apply to a larger group of testing assets which include both the carry trade and technology diffusion portfolios.

We also build a simple two-country environment to understand how the technology adoption accounts for the heterogeneous exposure and currency excess returns. The process of innovation and adoption follows Comin and Gertler (2006) and Comin et al. (2009). 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, all 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 optimally chooses 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 the endogenous resource reallocation between innovating and adopting sectors creates different risk exposures between the two countries. Under a positive shock, the home country expands the innovation effort. Its increase in production also benefits the foreign country 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 exports more expensive for the foreign economy, and consequently, the foreign country quickly shifts back to its innovation sector.

The presence of the adoption sector in the foreign country indicates its greater ability to shift risk towards the home country under global productivity risk. Importantly, we show that the endogenous re-balancing between innovating and adopting sectors creates an internal link between the two countries and produces an exchange rate dynamics supported by the data. Specifically, home consumption is more closely correlated with global output than foreign consumption. The difference in precautionary saving motives implies a positive interest rate spread and excess return on the carry trade (going long in the foreign currency and short in the home currency). 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 global productivity shocks, while the more R&D risks are shifted to the low-interest-rate countries.

Related Literature Recent advance in the literature suggests that the carry trade profitability can be attributed to a risk premium acquired by FX investors who seek to compensate themselves for adverse movements of the exchange rate under bad states of the world (e.g., Lustig et al., 2011a; Lustig and Verdelhan, 2007, etc.). Particularly, Lustig et al. (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 a basket of all available currencies each time and liquidates its position by borrowing the dollar. This strategy is mainly driven by the U.S. business cycle (e.g., Lustig et al., 2011b,0) thus, it is labeled as a dollar factor (DOL). 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 as it 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 not limited to Della Corte et al. (2016), Ready et al. (2017), Richmond (2019), Hassan (2013), Colacito et al. (2020), Jiang (2022), Filippou and Taylor (2017), Dahlquist and Hasseltoft (2020), and Menkhoff et al. (2012). In particular, Richmond (2019) uses a trade network model to justify that the low-interest-rate countries are usually more central to trade networks because their consumption growth is more exposed to the global consumption growth shocks. Ready et al. (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 currency risk premium and a persistent carry trade return. Similar to these two papers, we also use the trade flow data to construct our measure, but we emphasize the effect of R&D diffusion on the global productivity comovement and currency excess returns.

In addition, Hassan (2013) claim that countries' economic size (GDP share) is 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 low currency returns. 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 the government's intertemporal budget constraints. 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 et al. (2016) shows that countries' net foreign asset position (nfa) together with their currency structure of liabilities (ldc) can explain the cross-sectional variation in currency excess returns. Investors are compensated for holding net debtor countries' assets whose currency depreciates in bad times. Menkhoff et al. (2012) show 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 et al. (2020) provides 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.

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

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.[4] We construct an end-of-month series for daily spot and one-month forward rates as in Burnside et al. (2011). 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 are featured by strong CIP violations.[5] In the main analysis, we consider mid quotes, defined as the mean of the bid and ask quotes of each currency. In particular, the data are not averaged but represent the exchange rates on the last trading day of each month.

We denote by S_t and F_t as the spot and one-month forward exchange rates for a particular country, expressed in units of foreign currency per one U.S. dollar.[6] The log spot and forward exchange rates are respectively $s_t = \log(S_t)$ and $f_t = \log(F_t)$. Assuming that covered interest parity holds, we have that the forward discounts equals to the interest rate differentials; that is $f_t - s_t = \hat{i}_t - i_t$, where $\hat{i}_t$ and i_t are the nominal interest rates of the foreign country and the U.S. economy. The log excess return from t to t+1 (rx_{t+1}) is defined as the payoff from a strategy that buys a foreign currency in the forward market at time t and then sells it in the spot market after

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

[5]Figure C.8 in Appendix C shows the number of countries having data available through our sample episode.

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

one month. The excess return is expressed as

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

which can also be written as $rx_{t+1} = \left(\hat{i}_t - i_t\right) - \Delta s_{t+1}$. It says that the currency excess return comes from two parts: interest rate differentials and the rate of appreciation of the foreign 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 UN Comtrade. We adopt the six-digit level of disaggregation (based on the SITC code) to differentiate between manufacturing goods, raw materials, and natural resources and identify each product's technology level. Since our paper studies the effect of cross-country R&D spillover, we drop all the products other than manufacturing goods.[7] The R&D and GDP data are obtained from the World Bank Development Indicator (WDI). Quarterly consumption data comes 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.[8]

We use two samples for our analysis. The full sample consists of 27 OECD countries for which we have exchange rate and R&D data, and 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, Netherlands, New Zealand, Norway, Portugal, Slovakia, Slovenia, South Korea, Spain, Sweden, Switzerland, and the United Kingdom. The second group is a subset of the full sample and is considered the most traded and liquid currency in the FX market. These are ten currencies, including the U.S. dollar (referred to as "G10 Currencies"): Australia, Canada, 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 euro area countries are excluded after the introduction of the euro in January 1999. Some countries entered the eurozone after that date. In this case, their exchange rates are excluded from the samples at a later date. [9]

Tech-Diffusion Measure. The focus of this paper is to study the effect of R&D spillover across countries on their heterogeneous productivity risk exposures and consider its implication

[7] 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.

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

[9] 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 the bid-ask spread.

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 partner countries, it is likely to receive more technologies embedded in intermediate goods, which benefit the productivity in its own production.[10] It means that 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; Keller, 2004; Nishioka and Ripoll, 2012) construct measures in both the aggregate and disaggregate level to confirm that foreign innovation and the R&D content of trade contributes to the 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.[11] 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 GDP of both economies, $TI^{GDP}_{imp,exp} = TI_{imp,exp}/\left(GDP_{imp} + GDP_{exp}\right)$. Then, we multiply it by the R&D of the exporter country to consider the technology component of trade flows, which gives 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.[12] Specifically, denoting $EM_{imp,exp}$ as the extensive 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

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

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

[12]As defined by the tech-diffusion literature (e.g., Comin and Mestieri, 2010) and I paraphrase, "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."

trade openness;[13] that is

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

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 diffusion of technology across countries that are embedded in the quantity of trade per intermediate good. The measure accounts for the allocation of import flows from different trade partners.[14] We compute this measure for each country *imp* at time t and name 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 the 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 as they receive more on the R&D goods from their trade partners. On the other hand, low-interest-rate countries make R&D on themselves and export a 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 our tech-diffusion measure in the previous year $y-1$. The first portfolio contains the countries with a low concentration of R&D imports, while the last basket consists of currencies of high R&D import concentrations. 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 the currencies with the lowest forward discounts, named *funding currencies*, while the last basket consists of high-forward-discount currencies, and are called *investment currencies*. The spread of returns between the first and the last portfolios is the carry trade excess return.

[13] Coe and Helpman (1995) claim that the beneficial effect of foreign R&D spending to domestic productivity is stronger for counties more open to trade. Our measure can control for this effect.

[14] The value is higher for an importer who specializes its import to a single country than another importer who diversifies its import to multiple trade partners.

3 Baseline Empirical Results

This section presents the main empirical results. First, we discuss the relationship between technology diffusion, currency risk premium, and heterogeneous risk exposure. Then, we construct a tech-diffusion-sorted portfolio and use an asset-pricing model to price the currency risk factors. Lastly, we compare factors underlying conditional and 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 time average of tech-diffusion against the average forward discounts for our sample economies. 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. 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 larger 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 two groups of countries lead to a carry trade return? We find that the answer is yes from figure C.1 in Appendix C. The countries that adopt more technologies (e.g., Australia and New Zealand) also tend to generate a positive currency return against the U.S. dollar ($rx^{j,US} > 0$) in the carry trade portfolio. On the other hand, countries with low tech-diffusion indices (e.g., Japan and Germany) tend to have negative currency returns ($rx^{j,US} < 0$). From the lower panel of figure C.1, we can also conclude that the spread of currency returns is not completely driven by expected inflation. On average, the high-tech-diffusion countries enjoy a higher real interest rate than the U.S. ($r^j - rUS > 0$), while the real interest rate differentials are generally negative for the low-tech-diffusion economies ($r^j - r^{US} < 0$).

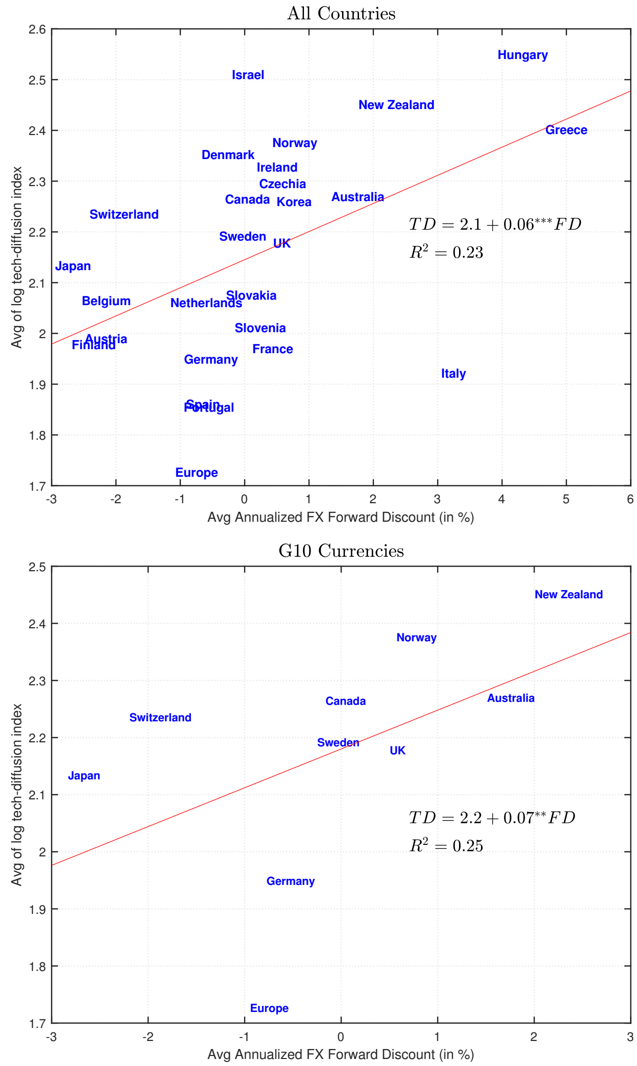
To test significance of the relationship between technology diffusion and currency returns, we run a list of cross-sectional regressions based on Fama and MacBeth (1973). Specifically, for each month t in each calender year y, we run the following cross-sectional regression,

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

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

Then, we average the coefficients across months. $rx_{i,t+1}$ is the return of investing in currency i from time t to time $t+1$ from an U.S. investor's perspective. $fd_{i,t} = f^i - s^i$ is the log forward discount of currency i against the U.S. dollar at time t. The explanatory variable is the log tech-diffusion measure, while we also control for the share of GDP, the (annualized) CPI-inflation, and the trade-volume-to-GDP ratio. The realized inflation is calculated as the percentage change of CPI over the previous year. We include the GDP share to control for the country size effect

Figure 1: Average Tech-Diffusion Index and Forward Discounts



Notes: The graph displays the average tech-diffusion indices (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".

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 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 of technology transmission on risk premium, which is the focus of this paper.

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

	All Countries				G10 Currencies			
Panel A: Fama-MacBeth Regression of FX Ret: rx_{t+1}								
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)
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)
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 the 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 parenthesis are Newey and West (1987) standard errors corrected for heteroskedasticity and autocorrelation (HAC) using 36 lags. Since part of 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, which contain monthly series from January 1993 to December 2019. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

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 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 one percent increase in our tech-diffusion measure induces a 0.3% percent increase in the currency return and a 0.25% increase in the forward discount. The effect of tech diffusion on the forward discount is more significant than on currency returns since exchange rate fluctuations are largely unpredictable. In addition, the result still holds after controlling for the country size, even though the point estimate suggests that larger economies tend to have lower currency returns and interest rates, which is consistent with 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 returns (from 26% to 70%). Most importantly, the relationship between country size and interest rate differentials (or currency returns) is dominated by our tech-diffusion measure. 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

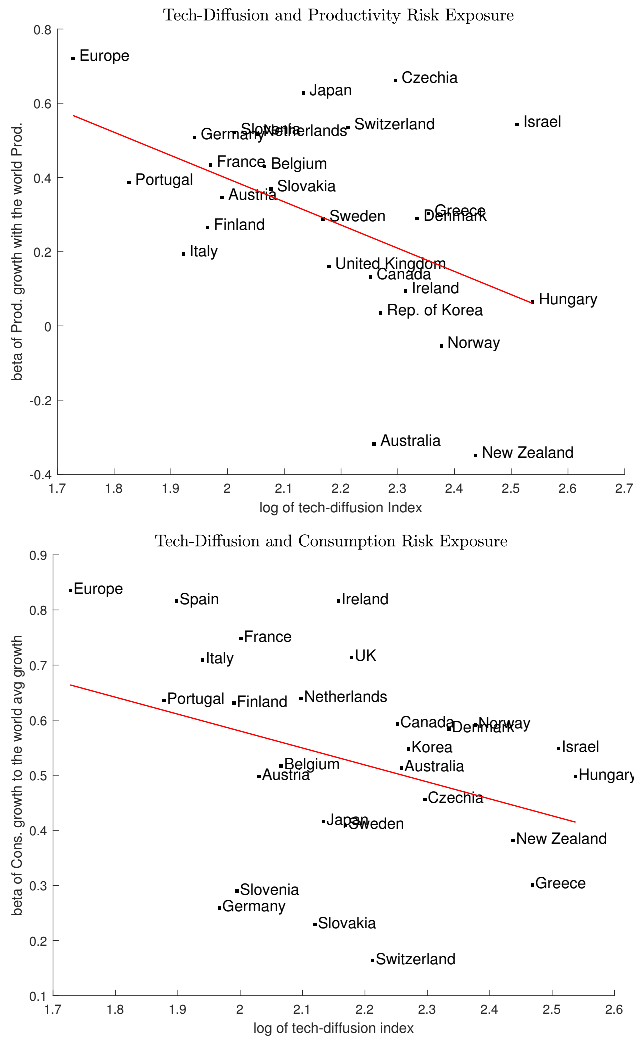
Having established the relationship between technology diffusion and interest rate differentials leads us to think about the economic mechanism behind it. Lustig and Verdelhan (2007) show that investors' exposure to aggregate consumption risk can account for the violation of the UIP condition and explains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

Figure 2 plots the countries' risk exposures against the average tech-diffusion measure. To derive the productivity risk exposure of 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 dataset of World Development Indicator. 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, Finland) tend to have a stronger comovement with the global growth cycle, while high-tech-diffusion countries (such as Norway, New Zealand, Hungary) are less exposed

Figure 2: Tech-Diffusion Index and Heterogeneous Risk Exposure



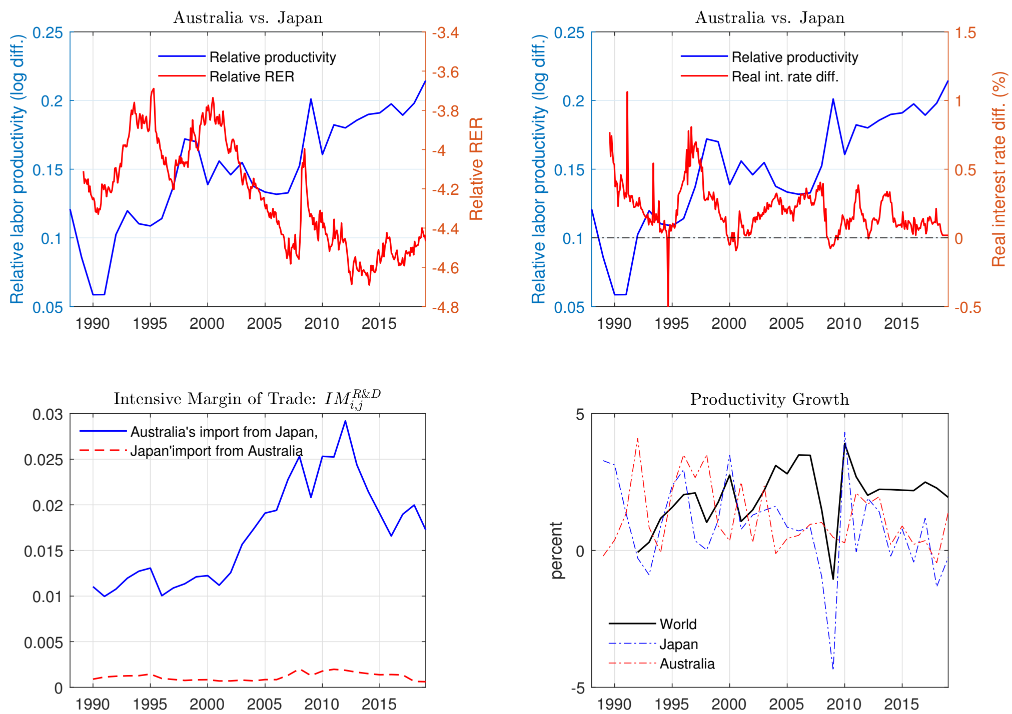
Notes: The figure plots the productivity growth (β_i^z) or consumption growth betas (β_i^c) for our sample countries against their average tech-diffusion measures (TD). A country's productivity growth beta is calculated by regressing the country-level productivity growth on the world productivity growth.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

to global shocks. Moreover, a comparison between upper and lower panels indicates that the impact of tech diffusion on risk exposures is stronger if we use productivity growth in the regression rather than consumption growth.[15]

To consider whether this relationship is quantitatively important, tables B.1-B.2 in Appendix B regress the productivity (or consumption) growth betas on tech-diffusion measures. We find that the cross-sectional difference in tech diffusion can still explain the heterogeneous risk exposure even

[15] Figures C.2-C.4 in Appendix C shows that the similar pattern holds for a broader set of countries or if we consider the consumption risk exposure to the U.S. economy.

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



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. Australia is considered a high-tech-diffusion country, while Japan is Australia's major trading partner aside from the eurozone.

when we control for country size, trade openness, and R&D volume. Adopting technologies through imports allows high-interest-rate countries such as Australia, New Zealand, and Norway to hedge against the global productivity risk.

How does the heterogeneous risk exposure account for the above-mentioned 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 vs. Japan.[16] Relative productivity is defined as the log difference in labor productivity between Australia and Japan. For a particular country, the real exchange rate (against the U.S.) is the nominal exchange rate adjusted by the relative CPI levels. The relative real exchange rate is the log difference in exchange rate indices between two countries. As shown in the upper left panel of figure 3, an increase in the relative real exchange rate indicates a real depreciation of the Australian dollar against the Japanese

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

yen. The real interest rate is calculated using the three-month forward discount subtracted by the four-quarters moving average of inflation.

From the bottom right panel of figure 3, we find that Japan has a stronger comovement with the global productivity shock than Australia. Australia's smaller risk exposure increased its relative productivity during the Global Financial Crisis around 2007-2008 (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 crisis, the expected appreciation of the Australian dollar lowered its interest rate by more than the interest rate of Japan. Overall, we find that Australia's relative real exchange rate is procyclical (appreciation of the Australian dollar in good times and depreciation 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 a fast growth during the boom period between 2000-2007 until it encountered a sudden stop in the Global Financial Crisis. Figures C.5-C.6 in Appendix C shows that the same mechanism applies to other country pairs such as New Zealand vs. Japan, Norway vs. Germany.

In sum, the heterogeneous global shock exposures across countries generate distinct risk profiles different currencies and produce 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 premium and technology diffusion.[17]

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 the previous-year tech-diffusion because the trade data from the UN Comtrade is reported with a time delay. For comparison, we also 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 $RX^i_{t+1} =$

[17] In the structural model in section 5, we show that the reallocation of resources between the innovation and adoption sectors allows the high-interest-rate countries to endogenously smooth their business cycle, resulting in smaller exposures to global productivity shocks.

$F_t^i - S_{t+1}^i$ as currency i's excess return in level, and the corresponding excess return of portfolio j is $RX_{t+1}^j = \sum_{i \in N_j} RX_{t+1}^i / N_j$. In the main text, we only consider construction of portfolios without transaction costs, since the tech-diffusion measure requires annual rebalancing and transaction costs are likely to be small.[18]

Panel A of table 3 provides 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-innovation" (AMI), and we contrast it with the traditional FX carry trade strategy (HML^{FX}) below.

Firstly, we notice 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. On average, the spread between high and low portfolios equals 2.41% for the full sample and 2.48% for G10 currencies. Secondly, the spread in forward discounts fully translates into the spread in currency excess returns, which contradicts the UIP condition. For both samples, investing in the high-tech-diffusion currencies earn positive excess returns. 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, and the number is similar between the two samples. Thirdly, 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.[19] It indicates that the spread of forward discounts is not entirely driven by the expected inflation channel.

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

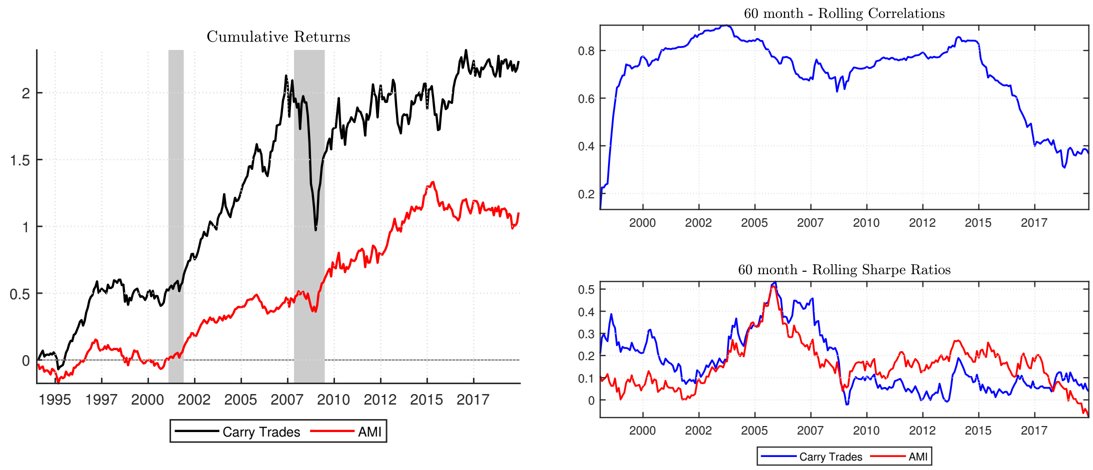
[19]Both the spread of forward discounts and the spread of real interest rates between the high and low portfolios are statistically significant at 1% level. Their t-statistics are omitted in the table.

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_j^z						Exposure to World Prod.: β_j^z					
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_j^z						Exposure to World Prod.: β_j^z					
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 summary statistics of quintile currency portfolios sorted on tech-diffusion measure (Panel A) and forward discount (Panel B). The first (last) portfolio P_L (P_H) comprise the 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 annualized mean, standard deviation (in percentage points), and Sharpe ratios. We also report forward discounts, real interest rate differentials, and productivity risk exposure of each portfolio. 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, which contain monthly series from January 1993 to December 2019.

Figure 4: Cumulative Returns and Rolling-Window Statistics



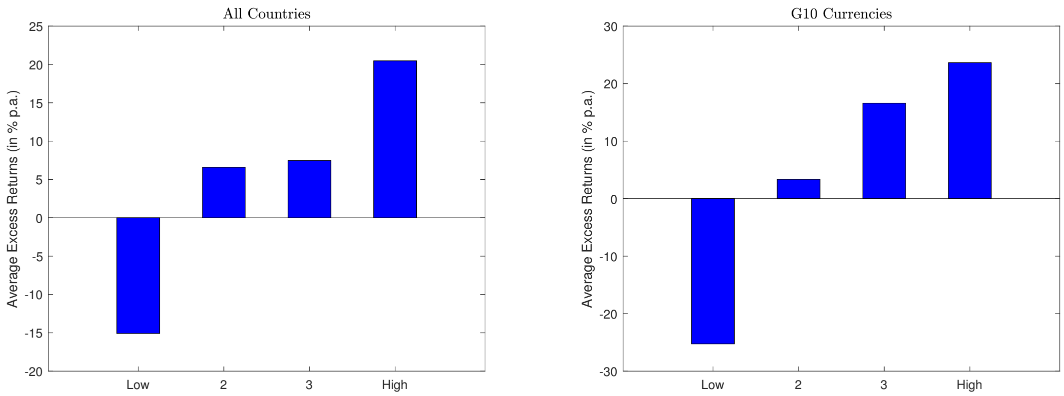
Notes: The left panel displays the cumulative returns from the carry trade and tech-diffusion-sorted (AMI) portfolios. The right panel displays (60-month) rolling-window correlations of the carry and AMI portfolios as well as their rolling-window Sharpe ratios. The data contain monthly series from January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

One thing to notice is that the spread of excess returns in the AMI strategy (2.82% and 3.50%) is higher than the spread of forward discounts (2.41% and 2.48%), which implies that high-tech-diffusion currencies tend to appreciate in the future and 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. Apparently, countries with the highest tech-diffusion index always enjoy the lowest risk exposure.

Panel B of table 3 reports the results of the carry trade portfolios. We find that both the currency returns and forward discounts follow similar patterns with the tech-diffusion-sorted portfolios. The spread in the average forward discounts is larger than 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. For both the full sample and G10 currencies, 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 expectation of future exchange rates. 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 portfolio. Lastly, countries with the lowest risk exposure are exactly the ones with the highest forward discount or real interest rate.

Cumulative Returns and Rolling Statistics. One key difference between 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. It suggests that

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.

the tech-diffusion may contain additional information about the risk premium than the forward discount. 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 afterward. The cumulative return of the AMI factor is much smaller due to the annual rebalancing, but it exhibits similar patterns to the carry trade strategy. In the right panel, we find that the correlation between carry and AMI factors goes up to 80% after 2000 and declines quickly since 2015. The rolling Sharpe ratios of the two strategies are closely connected. For both strategies, the Sharpe ratios are relatively high in the period between 2002 to 2008. Even though the carry trade strategy is more profitable, its larger volatility renders a similar Sharpe ratio to our AMI strategy.[20]

To better understand the relationship between currency carry trades and technology diffusion, figure 5 provides a visual illustration of the carry trade profitability conditional on technology diffusion. 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 of AMI realizations, 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. It suggests that the profitability

[20]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 upper and lower tail baskets are almost identical. For example, the Swiss Franc is considered a low-interest-rate currency in the carry trade portfolio, but Switzerland is not categorized as a low-tech-diffusion economy.

of carry trades strongly covary with our tech-diffusion strategy. To put it another way, sorting currencies based on 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), the excess return for any asset j satisfies the following Euler equation,

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

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_{t+1}^{j} is the currency excess returns for portfolio j at time $t+1$.[21]

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 (i.e., $\mu_\phi = \mathbb{E}(\phi_{t+1})$). Then, we can derive the beta representation of asset pricing model

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

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 price of factor risk 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. For each portfolio, its beta (β^j) can be derived by running a times-series regression of the portfolio excess return (rx_{t+1}^{j}) 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 linear version 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 my 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 (HAC) estimates of the long-run variance-covariance matrix of the moment conditions. The estimate of variance matrix is based on Newey and West (1987) methodology using the optimal number of lags.

In the second method, we perform a two-stage OLS estimation of Fama and MacBeth (1973)

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

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

	λ_{DOL}	λ_{AMI}	χ^2	R^2	$RMSE$		λ_{DOL}	λ_{AMI}	χ^2	R^2	$RMSE$
Panel A: Factor Prices											
	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)			

	α	β_{DOL}	β_{AMI}	R^2		α	β_{DOL}	β_{AMI}	R^2
Panel B: Factor Betas									
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 as well as Fama and MacBeth (1973) estimates of factor prices (λ). We also display Newey and West (1987) standard errors (in parenthesis) 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 regression with HAC standard errors in parenthesis. 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, which contain monthly series from January 1993 to December 2019.

(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 portfolios' average returns on the betas, period by period (without an intercept term). The factor price λ is the average of 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 can capture bulk proportion of this global risk factor and can account for most of the cross-sectional variation in average excess returns in carry-trade strategy. We assume a two-factor model of 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 factor of our interest that captures global shocks to the SDF. We use the portfolio that is long in high-tech-diffusion currencies and short in low-tech-diffusion currencies.

Panel A of table 4 shows results of cross-sectional asset pricing tests: the estimates of factor prices (λ), the joint tests for pricing errors, R^2 in the cross-sectional regression, and the root of mean squared error.[22] The left panel shows the results of 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} estimate are roughly the same under GMM method and under Fama and MacBeth (1973) (3.05 for the full sample and 2.34 for the G10 currencies). Moreover, χ^2 tests suggest that the cross-sectional pricing errors are insignificant, which indicates 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, 69% for the full sample, and 52% for the G10 currencies. The square root of the mean square error is larger for the estimation of G10 currencies (0.92) than the sample of OECD countries (0.69).[23]

One thing to notice is that the estimate of dollar factor price (λ_{DOL}) is negative in all specifications and statistically insignificant. This is due to the fact that the global interest rates are largely affected by unconventional monetary policies such as quantitative easing after the Global Financial Crisis. That lowered all currency returns in the market portfolio. Table B.6 in Appendix B provides the results of asset pricing tests separately considering the samples before and after the Global Financial Crisis. We find that for both the full sample and the G10 currencies, the price of level factor becomes positive if we only use the sample before 2008. Apart from that, the price of the slope factor (λ_{AMI}) is more significant than the baseline results. In addition, table B.5 in Appendix B shows asset pricing results when we include both carry-sorted portfolios and tech-diffusion-sorted portfolios as test assets to maximize the power of the tests. We notice that the estimate of factor

[22]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 shows the pricing error plots at the portfolio level. We find that our model offers a strong fit as most of the portfolios are closely aligned with the 45-degree line.

[23]Figure C.15 in Appendix C shows the pricing error plots for 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.

price (λ_{AMI}) becomes smaller but more significant due to reduced standard errors. Overall, we find strong evidence that the carry trade portfolios are associated with heterogeneous exposures to a common risk factor, and our candidate factor constructed using tech-diffusion measure has significant predicting power for the cross-sectional currency excess returns.

Time-Series Analysis. Panel B of table 4 also displays estimates of 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 tail portfolios are also highly significant, as indicated by the HAC standard errors. However, the difference in exposures 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%-85% using the full sample and 65%-82% using the G10 currencies.[24] After all, this structure of portfolio betas provides us the evidence that the carry-trade-sorted portfolios are characterized by heterogeneous exposures to a common global risk factor that is related to the international spillover of technology innovation.

3.5 Beta-Sorted Portfolios

Our baseline exercise in table 4 indicates that the forward-discount-sorted portfolios (carry) generate a structure of heterogeneous exposures 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.[25] 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 at time t based on their sensitivity to the global factor. Portfolio 1 contains currencies with a negative exposure to the tech-diffusion factor, and Portfolio 5 includes currencies with positive exposures. Table 5 reports summary statistics of beta-sorted portfolios. Panel A shows results for all countries, and Panel B displays results for G10 currencies.

First, we find that the average forward discounts increase monotonically from the low-beta economies to the high-beta ones. A larger sensitivity to global shocks makes currencies in the last

[24] Figure C.18 of Appendix C provides estimation 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 carry trade high-minus-low strategy (HML^{FX}_t) demonstrates the strong pricing ability of our tech-diffusion measure.

[25] 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-Months Windows

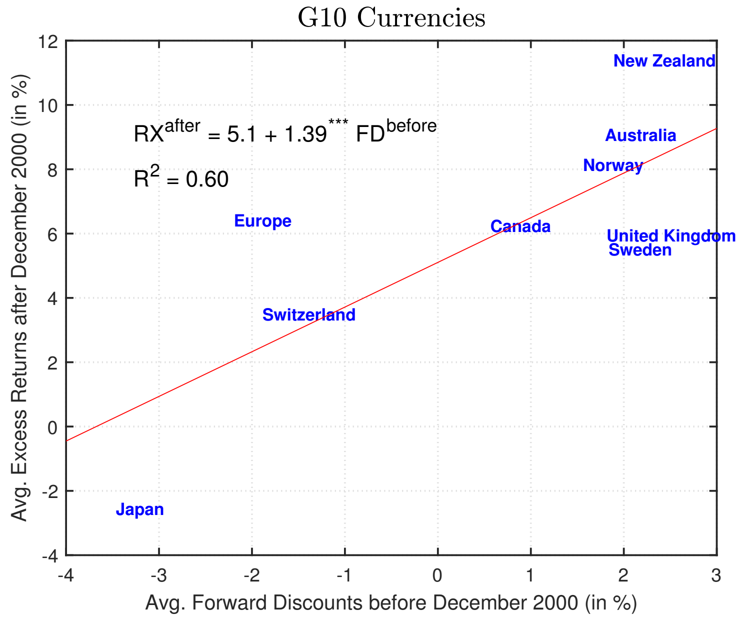
Panel A: **All Countries**							
	P_L	P_2	P_3	P_4	P_H	Avg	H/L
Mean	−1.76	0.29	−0.50	0.09	2.44	0.11	4.21
	[−0.91]	[0.15]	[−0.27]	[0.05]	[1.00]	[0.06]	[2.67]
Sdev	7.70	8.71	9.01	9.06	11.19	8.24	9.06
SR	−0.23	0.03	−0.06	0.01	0.22	0.01	0.46
Skew	0.08	−0.35	−0.17	−0.22	−0.73	−0.25	−0.79
Kurt	3.06	3.87	4.07	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 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 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.

portfolio a risky investment from the U.S. investors' perspective, causing a higher risk premium. Therefore, sorting based on the forward discounts and sorting based on risk exposures (betas) are clearly related. It also implies that the forward discount may contain information about the riskiness of an individual currency. Moreover, the average excess returns also tend to increase 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 sorting.

The last three lines in each panel show the pre- and post-formation betas and the average tech-

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 1/1993 and 12/2000. The y-axis is the average excess return of each currency between 1/2001 and 12/2007. We cut the data after the Global Financial Crisis. The data are collected from Datastream *via* Barclays and Reuters.

diffusion indices for each portfolio. The pre- and post-formation betas vary monotonically from the first to the last portfolio, indicating that the rebalancing of portfolios based on this sorting strategy is infrequent. The average tech-diffusion indices also increase with the betas. It suggests that the currencies that covary more with our AMI factor come from the countries with high-tech-diffusion measures.

3.6 Unconditional Currency Returns

Since the international transmission of R&D is a slowing moving factor for the currency risk premium, for most countries, our tech-diffusion measures are quite stable over time. It is important to consider by how much proportion the tech-diffusion factor (AMI) can be used to explain the unconditional carry trade returns rather than conditional ones. We construct the unconditional carry trade portfolios using the average 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 are largely suppressed by a series of monetary easing policies after that date. Figure 6 plots the average excess returns of G10 currencies from 2001 to 2007 (denoted as RX^{after}) against their mean forward discounts in the first-half sample (denoted as FD^{before}). We find that the average forward discount in the first-half sample is a strong positive predictor of countries' future currency excess returns. The fitted line explains 60% of its cross-sectional variation.

Panel A of table 6 shows summary statistics of conditional carry trade portfolios sorted on the first-half sample mean forward discount. 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 turns in the second-half sample with a spread of 9.66% (6.74%) in the full (G10) sample, even though smaller than the return spread produced by conditional sorts of the same episode (10.22% and 10.13%). The premium on unconditional carry trade strategy is statistically significant, with a Sharpe ratio even larger than one. Moreover, the forward discount implied by unconditional carry is also monotonic from the first to the last, indicating that interest rates are persistent for individual currencies.

Table B.7 in Appendix B shows the conditional and unconditional sorts based on the half-sample average or previous-year tech diffusion. The unconditional tech-diffusion strategy is labeled as $UAMI$. We notice that the return spread implied by the unconditional AMI strategy still runs short of the conditional AMI strategy, but the difference between these two is smaller than the carry trade returns. The reason is that our tech diffusion is a long-run factor, and countries' ranking has small turnovers across the sample episode.

Table 6: Summary Statistics: Carry Trade Portfolio Sorts 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 summary statistics for quintile currency portfolios sorted on the average forward discount between 1/1993 and 12/2000 (Panel A) or the previous-month forward discount (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) comprises the 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 sells P_L of portfolios. Moreover, the table presents 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 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 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 1/2001 and 12/2007. We use as test assets the five carry trade portfolios sorted on the first half-sample mean forward discount between 1/1993 and 12/2000.

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 a 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.[26] Specifically, the factor price estimates (λ_{AMI}) are always positive and highly significant in both samples. Regarding the goodness of fit, 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 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 of the DOL factor are always close to one as it serves as a level factor. The coefficients of the AMI factor increase almost monotonically from the first to the last portfolios, indicating the heterogeneous risk exposures of unconditional portfolios.

Next, we consider by how much proportion the return of AMI strategy can be used to explain

[26] Table B.8 in Appendix B shows results of asset pricing tests when we use DOL and $UAMI$ as risk factors. We find that the unconditional tech-diffusion factor still has predicting power for the unconditional carry trade returns. This is evidence that the spread in returns on both tech-diffusion-sorted portfolios and carry portfolios are driven by the difference in exposure to a common source of risk.

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 results of the time-series regression: $fac_t = \alpha + \beta AMI_t + \gamma fac_{t-1} + \epsilon_t$. The estimate of γ is omitted in 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 /1993 and 12/2007 based on the previous-month forward spread. $UHML^{FX}$ is the unconditional carry trade return sorted on the mean forward spread between 1/1993 and 12/2000. The currency excess returns are calculated based on the second-half sample from 1/2001 to 12/2007. For comparison, $HML^{FX}(2)$ is the conditional carry trade return only on the second-half sample. Standard errors in parentheses are based on Newey and West (1987). *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

the unconditional returns on currency carry trade ($UHML^{FX}$). To do that, we fun the following time-series regression:

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

where fac is the excess return of either HML^{FX} or $UHML^{FX}$. To compare 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 in all specifications that AMI is highly correlated with the carry trade strategies and beta coefficients are all significant. However, the unexplained currency excess returns (alphas) are more significant for conditional strategies than unconditional carry trade strategies. The result implies that the returns on conditional carry trade may contain more information than the unconditional returns, and sorts on tech diffusion unveil the heterogeneous exposures to a common risk factor which is unconditional in its nature.

4 Additional Results

This section first provides an alternative sorting strategy for the international technology transmission 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 measures the trade concentration of an R&D recipient country, weighted by the innovation efforts 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 in the home (tech-adoption) country. In this section, we follow method of Della Corte et al. (2016) and Cespa et al. (2022) to construct a (2×3) double-sorting strategy based on importers' R&D ratio and trade concentration (not weighted by R&D), respectively.[27]

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

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

where the intensive margin of trade is not adjusted by R&D from its trade partners; that is $IM_{imp,exp} = TI_{imp,exp}/EM_{imp,exp}$. Then, we construct the double-sorting portfolios as follows: at the end of each period t, we first group currencies into two baskets using countries' R&D ratios; then, we reorder currencies within each basket using the above-defined trade concentration (TC). 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 countries that receive a high trade concentration, and P_{21} represents high R&D countries with a low concentration. We construct the returns of a double-sorting strategy (referred to as $AMI^{2\times3}$), making investors go long currencies 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 summary statistics of the double-sort portfolios. 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 monotone across the second sorting dimension: $[P_{11}, P_{12}, P_{13}]$, $[P_{21}, P_{22}, P_{23}]$. Most importantly, we find that the double-sorting strategy generates a positive and significant spread of currency returns: $AMI^{2\times3} = P_{13} - P_{21}$. Compared to the sorts 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 trade concentration measure, especially in the high R&D group. Figure C.17 in Appendix C contrasts the cumulative returns of double-sorts and tech-diffusion measures. The correlation between the two factors 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 performance as our baseline model, they contain different information. Double-sorting considers the importers' R&D while the tech diffusion considers exporters'. Through the double-sorting, we

[27] Della Corte et al. (2016) consider a 2×3 double-sorting strategy based on countries net foreign asset and proportion of liabilities denominated in foreign currencies. Cespa et al. (2022) consider a 3×3 double-sorting strategy based on the previous-24 hours currency returns and FX transaction volumes.

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 summary statistics of 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 a long-short strategy that buys P_{13} and sells P_{21}. The table presents 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 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, which contain monthly series from January 1993 to December 2019.

select the countries with a low effort of innovation but actively importing manufacturing goods, and it turns out that the currencies of these countries have higher returns than their counterparts, the countries conducting many innovations but more reluctant to import manufacturing 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 this double-sorting is an indirect measure, ranking countries based on their R&D intention and trade connection.[28]

[28]Figure C.10-C.13 in Appendix C compares the portfolio turnover rates of the two sorting strategies. The identity of currencies in both tail portfolios mostly coincide, but there are several exceptions. For example, the euro is almost always considered as a funding currency under tech-diffusion sorts, but sometimes it is missed under double-sorts. The opposite is true for the Swedish krona.

Table B.9 in Appendix B shows asset pricing tests using the return on double-sort as a risk factor. The estimate of factor price is always positive and significant, and the estimation is more precise than the baseline case based on the tech-diffusion factor (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 ($\beta_H - \beta_L = 0.68/0.82$ vs. $0.54/0.62$), indicating that the double-sorting strategy is more able to capture the heterogeneous risk exposures underlying the two tail portfolios.

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-related 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 construed based on the countries' import ratio[29]. 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). Secondly, we consider the PMC factor of Richmond (2019), which is the return on a portfolio that buys currencies of central countries and sells currencies of peripheral economics. Since central countries are more exposed to the global consumption risk, the returns of their currencies are lower than the periphery economies. To facilitate the comparison, we consider the reverse strategy of PMC (denoted as $PMC^{(-)}$). Moreover, in this section, we use Ready et al. (2017)'s sample of 22 countries - a subset of our sample and Richmond (2019)'s sample.

Table 10 shows summary statistics of all the three trade-related currency risk factors, together with the carry trade returns.[30] We notice that both 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. 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 all the other factors. AMI factor exhibits the smallest disaster risk: the maximum drawdown is smaller than IMX and HML^{FX}.

Figure C.19 in Appendix C provides a visual illustration of the relationship between the three factors by showing countries' relative rankings. We find that the rankings based on tech diffusion and 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

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

[30]Table B.10 in Appendix B shows the correlations between alternative risk factors. We find that all factors exhibit moderate correlations with each other. Relatively, the AMI factor is more tightly correlated with IMX (0.62) than $PMC^{(-)}$ (0.53). Among the three trade factors, IMX has the strongest correlation with the carry HML^{FX} (0.64).

Table 10: Summary Statistics of Alternative Currency Risk Factors

	HML^{FX}	AMI	IMX	$PMC^{(-)}$	$AMI^{2\times 3}$
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 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 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.

and centrality is looser than the connection between tech-diffusion 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 periphery to the trade network.

The results in table 10 and figure C.19 show that the three trade 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 to explain the cross-section of currency returns.[31] To do that, we first regress the AMI factor on IMX or PMC and extract the estimated residuals (denoted as $AMI^{\perp IMX}$ and $AMI^{\perp PMC}$). Then, we include the orthogonalized risk factors in the asset pricing model together with the dollar factor to consider their predictabilities.

Table 11 displays the asset pricing tests for orthogonalized risk factors.[32] The left panel shows the results of the IMX, while the right panel shows the PMC. In both cases, the orthogonalized factor still has strong predicting power for the cross-sectional 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 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 Fama and MacBeth (1973). The five carry portfolios have heterogeneous exposures on our residual factors, although the betas

[31] The data used to construct the AMI factor is very different from the IMX factor as we focus on the transmission of technology across the border, which is embedded in the trade of manufacturing goods, and we exclude data of raw materials.

[32] 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 Factor: 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 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 tech-diffusion factor orthogonalized to Ready et al. (2017)'s commodity trade factor, while $AMI^{\perp PMC}$ represents the part of 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 covers from 1/1993 to 12/2012 for the IMX factor and from 1/1993 to 12/2016 for the PMC factor. Panel A reports GMM_1, GMM_2 as well as Fama and MacBeth (1973) estimates of factor prices (λ). Panel B reports OLS estimates of contemporaneous time-series regression with HAC standard errors in parenthesis.

are not monotonic for the orthogonalization on IMX.

5 A Simple Model of Tech-Diffusion

This section builds an analytic two-country model to consider how the heterogeneous exposure to global shocks generates currency risk premium. The process of innovation and adoption follows Comin and Gertler (2006) and Comin et al. (2009). The economy lasts for two-period: $t = 1, 2$. In the first period, agents receive endowments and decide on innovation and adoption investments. Productions happen 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 patent or adopt patent from home.[33] The innovation and adoption are modeled as the love-of-variety processes as in Romer (1990). In country-F, the size of innovating (adopting) sector is a constant μ $(1 - \mu)$.

[33] Online Appendix shows a version of the model that 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 in the foreign country.

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, in country-F, the relative benefits of adopting and innovating depend on the cost of intermediate goods and the real exchange rate. In the following, we will use this model to show that the endogenous resource reallocation between innovating and adopting sectors creates an internal link between the two countries and produces an exchange rate dynamic that is close to the data.

We assume that the productivities are persistent and follow a bi-variate 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 investment decisions. In period 1, we assume $y_1^h = z^h$, $y_1^f = z^f$.[34]

The Second-Period Problem In period 2, the final goods are produced with intermediate goods using production functions as follows,

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

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

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 adoption in country-F, using one imported intermediate good ($x_{h,2}^f$) costs $1/e_2$ units of final consumption. e_2 denotes the second-period real exchange rate, which represents the units of consumption good in country-H for each consumption good in country-F.[35]

In addition, final goods can be transported across the border but with a shipping cost. For X_2 units of consumption goods exported by country-F, the country-H only receives $X_2\left(1 - \frac{\kappa}{2}X_2\right)$ in the unit of its own consumption. There is a continuum of competitive final good 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 real exchange rate always equals one:

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

[35] An increase in e_2 indicates a real depreciation of the home currency.

$e_1 = 1$. 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,

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

Then, production of outputs is given by,

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

We notice that a home currency depreciation reduces the cost of adoption and increases the foreign output.

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:[36]

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

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 of Comin and Hobijn (2010) and Comin et al. (2014).[37]

We suppose a social planner maximizes the global welfare,

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

[36]Comin and Gertler (2006) and Santacreu (2015) consider the adoption's success rate as an increasing function of its adopting effort. Here, we use the cost function set-up to derive analytical solutions.

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

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 technology in the two-country environment.[38] In particular, her problem is to choose the allocations of $\{c_1^h,\ c_1^f,\ N_2^h,\ N_2^f,\ N_{h,2}^f,\ c_2^h,\ c_2^f,\ X_2,\ x_2^h,\ x_2^f,\ x_{h,2}^f\}$ that maximizes the global welfare (22) subject to equations (14), (15), (19), (16), (17), (18), and (23).

Taking derivatives yields the following first-order conditions for the social planner,

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

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

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

where $\tilde{\xi} = \xi^{\frac{\xi}{1-\xi}} - \xi^{\frac{1}{1-\xi}}$. We have the expressions of pricing kernels and risk-sharing condition as follows,

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

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

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 version. Denote $\hat{x}$ as the log-deviation of variable x around its deterministic steady state. To facilitate our analytical derivation, we first make the following assumption.

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

[38] 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.

The assumption of preference and the risk-neutrality simplifies the formulas of interest rate and allows us to characterize the properties of the model.[39] In addition, since country-H's innovation has an externality on country-F's adoption cost, 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 innovations. In the second period, its depreciated exchange rate increases the export of intermediate goods and benefits country-F's adoption sector. The following assumption excludes this inter-temporal financial flow channel and simplifies the solution.

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

Based on these assumptions, the optimality conditions of innovation and adoption in equations (24)-(26) can be re-expressed as the following,

$$\hat{N}^h_2 = A_1 \hat{z}^h + A_2 \hat{z}^f + A_3 \hat{e}_2, \tag{28}$$

$$\hat{N}^f_2 = \frac{1}{\eta}\frac{1}{1-\xi}\hat{z}^f, \tag{29}$$

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

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)-(18) and using the risk-sharing condition (27), we have the following expressions of exchange rate and consumption

[39] Online Appendix shows extend the model to the general CRRA utility and risk-averse firms where we can see all the mechanisms in this section still work.

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 depends on the realization of shocks.

Lemma 1. *Under the conditions that (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 have that the real exchange rate of country-H depreciates if there is a positive shock on the common productivity between country-H and country-F; that is* $\frac{\partial \hat{e}_2}{\partial \hat{z}} > 0$*, if* $\hat{z}^h = \hat{z}^f = \hat{z}$*. Also, the real exchange rate depreciates if there is a positive mean-preserving productivity shock; that is* $\frac{\partial \hat{e}_2}{\partial \hat{\epsilon}} > 0$*, if* $\hat{z}^h = -\hat{z}^f = \hat{\epsilon}$*.*

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 hedge for an international currency investor. The first condition is a regularity condition. The second condition holds only when the adoption elasticity parameter 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, country-H's consumption increases by more than country-F when there is a positive shock on the common productivity in two countries; that is* $\frac{\partial \hat{c}_2^h}{\partial \hat{z}} > \frac{\partial \hat{c}_2^f}{\partial \hat{z}} > 0$*, if* $\hat{z}^h = \hat{z}^f = \hat{z}$*. Also, a mean-preserving productivity shock increases the global output; that is* $\frac{\partial \hat{y}_2}{\partial \hat{\epsilon}} = \frac{1}{2}\frac{\partial(\hat{c}_2^h+\hat{c}_2^f)}{\partial \hat{\epsilon}} > 0$ *if* $\hat{z}^h = -\hat{z}^f = \hat{\epsilon}$*.*

Proof. See Appendix A.2. □

The first part of the lemma 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 states where country-H's productivity is higher than country-F. Or put it another way, the global business cycle (i.e., the fluctuation of total 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 on 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 3. *Suppose that the conditions (i)-(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

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

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

Also, 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 3 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 positively comove with the global output. We have this currency risk structure because the two countries have heterogeneous exposure to global shocks (as in lemma 2). The condition (iii) holds when the size of the adoption sector $(1-\mu)$ is not too large. The following proposition describes the correlation of SDF and the cyclicality of intermediate export.

Proposition 4. *Suppose that conditions (i)-(iii) hold. Then, the correlation of SDF is higher than the correlation of productivity shocks; that is*

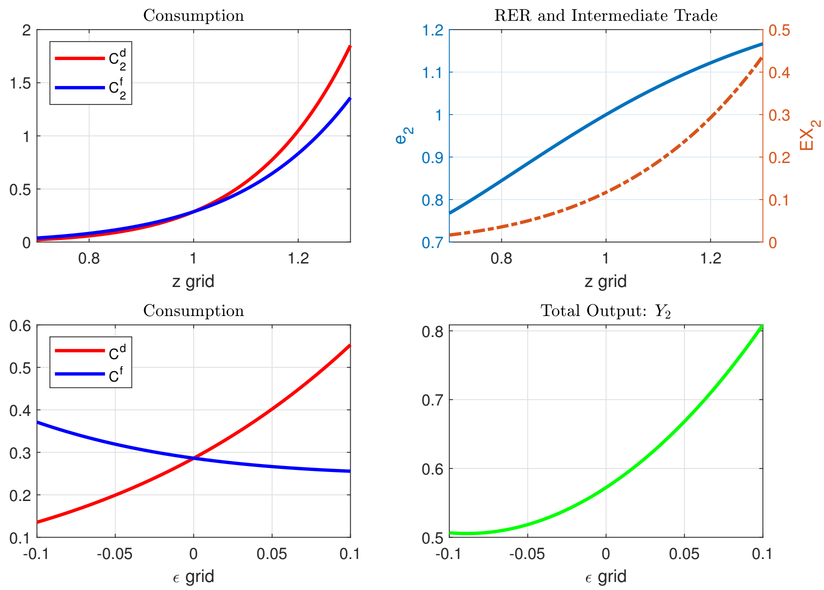
$$corr(m_2^h, m_2^f) = corr(\hat{c}_2^h, \hat{c}_2^f) > corr(z^h, z^f). \tag{37}$$

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

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



NOTE: This picture shows the functions of consumption, exchange rate, and world production in the simplified model. The parameter values are: $\sigma = 0.5$, $\mu = 0.5$, $\xi = 0.45$, $\eta = 0.35$, $b_1 = 2$, $b_2 = 0.3$. In the upper panel, we consider a common productivity shock between 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 $\hat{z}^h = -\hat{z}^f = \hat{\epsilon}$.

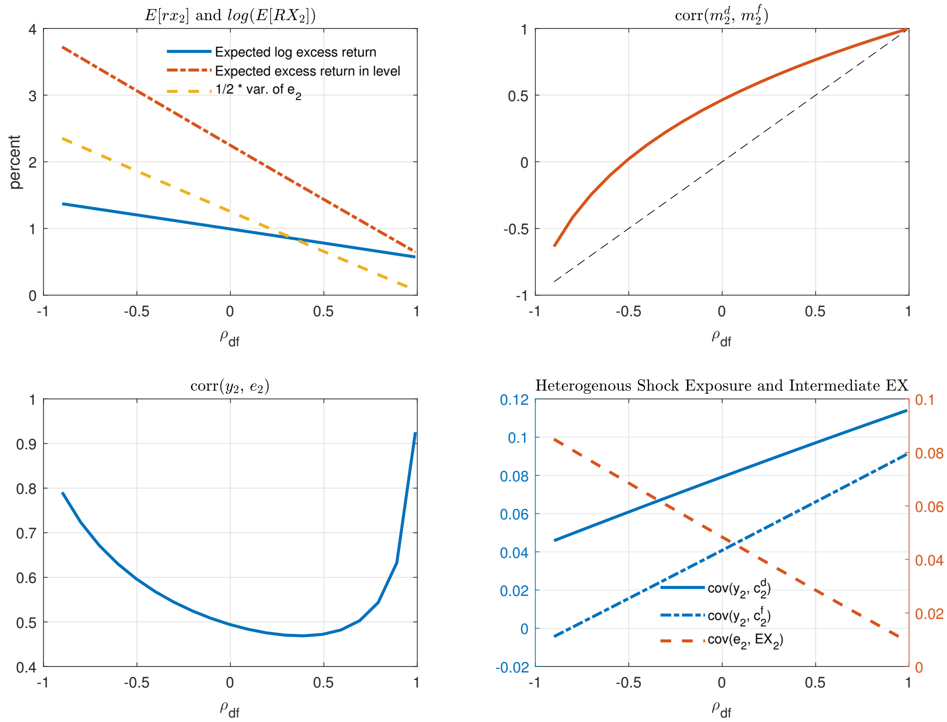
5.2 Numerical Illustration

Figure 7 provides a numerical illustration of the model by showing the functions of consumption, output, 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 exposed to global shocks (in both the dimension of z and ϵ). Second, country-H leads the business cycle. The good states are always accompanied by 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 also stimulates the intermediate exports to its trade partner.

Figure 8 shows the predicted moments of the model for different level of shock correlation ρ_{fd}. The comparative statics by varying the size of adoption sector $(1 - \mu)$ is shown in figure C.20 in Appendix C. 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, thus decreasing the risk premium. In the upper right panel, we find that due to the endogenous tech diffusion, the cross-country correlation of SDF between the two countries is always larger than the correlation of shocks.

In the bottom left panel, we find that the cyclicality of the exchange rate (also the cyclicality of excess return) is not monotone in ρ_{fd}. Specifically, a mildly positive shock correlation (ρ_{fd}

Figure 8: Predicted Model Moments for Diff. Shock Correlation ρ_{df}



NOTE: This picture shows model-implied moments for 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.

at around 0.5) produces a minimized exchange rate-output correlation. The bottom right panel shows that home consumption is always more exposed to the global business cycle than foreign consumption, and the difference in the two correlations (solid and dashed blue lines) gets narrower as productivity shocks more strongly comove. Moreover, a larger ρ_{fd} also mitigates the correlation between the exchange rate and intermediate exports.

6 Conclusions

In this paper, we study the role of technology diffusion in the foreign exchange market. Particularly, we link technology diffusion with the carry trade activity. Carry trade is a foreign exchange strategy that goes long in the high-interest-rate currencies and short in the low-interest-rate currencies. Tech-diffusion is defined as the concentration of R&D in the imports of intermediate goods. We develop a two-factor asset pricing model that incorporates information on the dollar factor and global technology diffusion factor. The tech-diffusion factor is a zero-cost portfolio that involves a long position in high-tech-diffusion portfolios (i.e., adopters' currencies) and a short position in low-tech-diffusion portfolios (i.e., innovators' currencies). We find that tech-diffusion factor is priced in the cross-section of the carry trade portfolios. Intuitively, carry traders require a risk premium for taking on R&D risk. We rationalize our findings in an asymmetric two-country two-period model. The model can account for countries' heterogeneous risk exposure to the global productivity shocks and implies a persistent currency risk premium.

The results are robust to different specification tests. The pricing ability is also verified by beta-sorted portfolios, where a positive and statistically significant spread is obtained. We show that technology diffusion contains important information for both conditional and unconditional currency returns. The result still holds after controlling for transaction costs of the carry trade. Finally, we extend the cross-section of currency portfolios and find that technology diffusion can price carry trade and technology diffusion portfolios.

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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

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

$$\iff$$

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

$$\iff$$

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

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

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

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 3

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 3 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 4

Proof. **The first half:** By the definition of $\hat{z}$ and $\hat{\epsilon}$ in the proof of proposition 3, we have the following,

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

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

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

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

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

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

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,

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

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 $\operatorname{corr}(\hat{y}_2, \hat{EX}_2) > 0$ (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 $\operatorname{corr}(\hat{y}_2, \hat{EX}_2)$ 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 $\operatorname{corr}(\hat{y}_2, \hat{EX}_2) > 0$ at all $\rho \in [-1,1]$; or $\operatorname{corr}(\hat{y}_2, \hat{EX}_2) > 0$ 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 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 in 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 parenthesis are Newey and West (1987) standard errors corrected for heteroskedasticity and autocorrelation (HAC) using 36 lags. *, **, and *** denote significance at the 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 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 in 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 parenthesis are Newey and West (1987) standard errors corrected for heteroskedasticity and autocorrelation (HAC) using 36 lags. Standard errors in parentheses are clustered by country. *, **, and *** denote 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 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) comprise the 20% of all currencies with the lowest (highest) value of tech-diffusion measure or forward discount. HML is the a long-short strategy that buys P_H and sells P_L. Moreover, the table presents 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, which contain monthly series from January 1993 to December 2019.

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

All Countries							
	P_L	$P2$	$P3$	$P4$	P_H	Avg	H/L
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 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 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 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., 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 parenthesis) corrected for autocorrelation and heteroskedasticity with optimal lag selection. Sh represents the corresponding values of Shanken (1992). The table also shows 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 parenthesis. 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, which contain monthly series from January 1993 to December 2019.

Table B.6: Sub-samples Before and After 2008

	λ_{DOL}	λ_{AMI}	χ^2	R^2	$RMSE$	λ_{DOL}	λ_{AMI}	χ^2	R^2	$RMSE$
Panel A: Factor Prices Before 2008										
	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 asset pricing results for the two-factor model when we divide our sample into two episodes. Panel A uses the sub-sample before the Global Finance Crisis (1/1993 - 12/2007); while Panel B uses the sub-sample 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 as well as Fama and MacBeth (1973) estimates of factor prices (λ). We also display Newey and West (1987) standard errors (in parenthesis) corrected for autocorrelation and heteroskedasticity with optimal lag selection. *Sh* represents 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 χ^2 tests.

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

	Panel A: Sorted on Average Technology 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 Technology 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 summary statistics for quintile currency portfolios sorted on the average tech diffusion over the sample 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 the 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 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 asset pricing results for the two-factor 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 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 asset pricing results for the two-factor model that comprises the 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 parenthesis) corrected for autocorrelation and heteroskedasticity with optimal lag selection. Panel B reports OLS estimates of contemporaneous time-series regression with HAC standard errors in parenthesis. The currency data are collected from Datastream *via* Barclays and Reuters, which contain monthly series from January 1993 to December 2019.

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

	HML^{FX}	AMI	IMX	$PMC^{(-)}$	$AMI^{2\times 3}$
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	
$AMI^{2\times 3}$	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 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 previous-year import ratio (as in Ready et al., 2017) and goes long in high-import-ratio currencies (commodity country) and short in low-import-ratio currencies (producer country). HML^{FX} is the conditional carry trade factor. $AMI^{2\times 3}$ is the double-sorting strategy based on the R&D ratio and trade concentration. We use the sample of 22 countries of Ready et al. (2017).

Table B.11: Cross-Sectional Asset Pricing for RRW Sample (i.e., 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 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 as well as Fama and MacBeth (1973) estimates of factor prices (λ). We also display Newey and West (1987) standard errors (in parenthesis) 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 regression with HAC standard errors in parenthesis. The alphas are annualized. The currency data are collected from Datastream *via* Barclays and Reuters, which contain monthly series from January 1993 to December 2019.

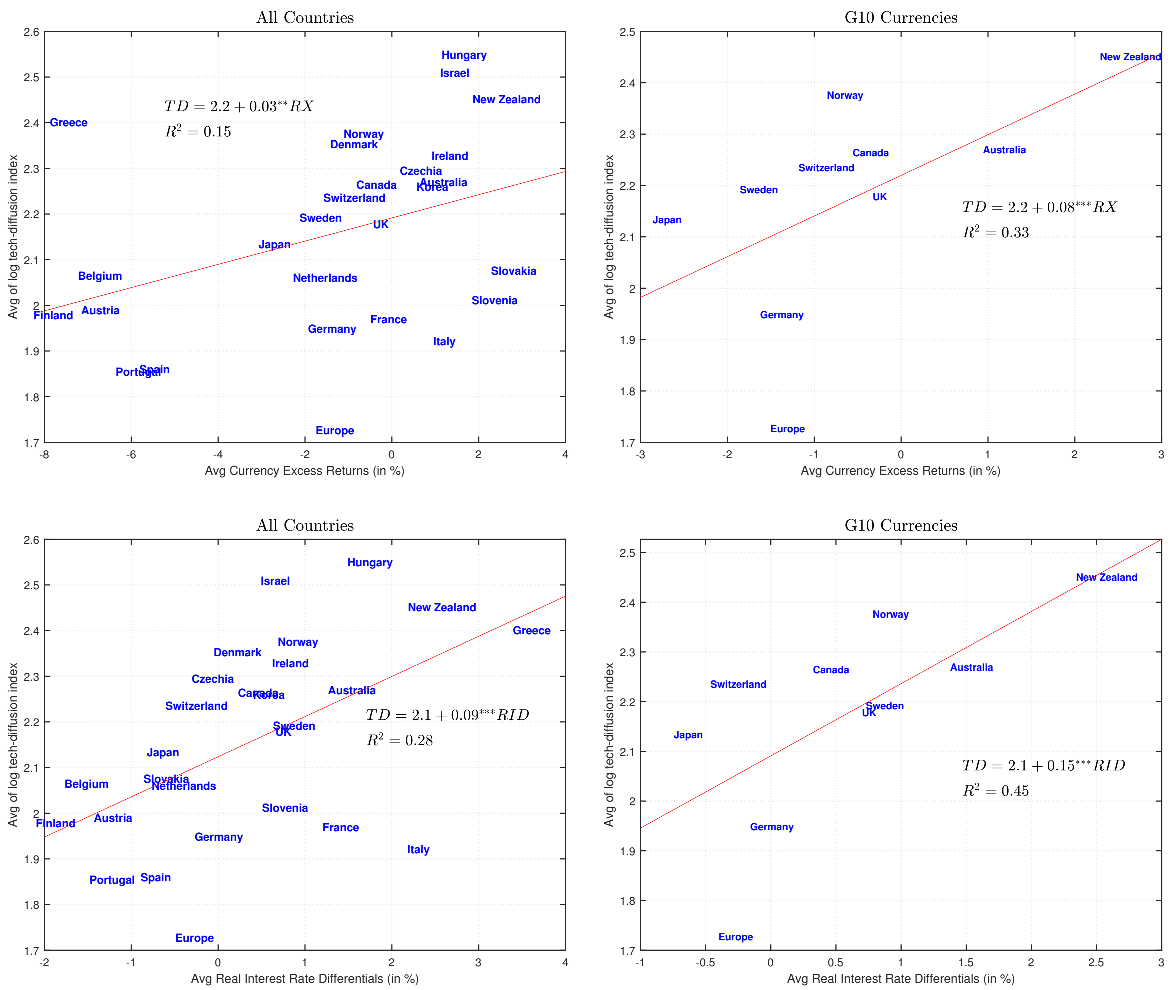
Table B.12: Conditional Asset Pricing Using Rolling-Window Regression

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 market prices of risk, the square root of mean-squared errors (RMSE), and χ^2 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 parenthesis are based on Newey and West (1987). The sample period covers from January 1993 to December 2019.

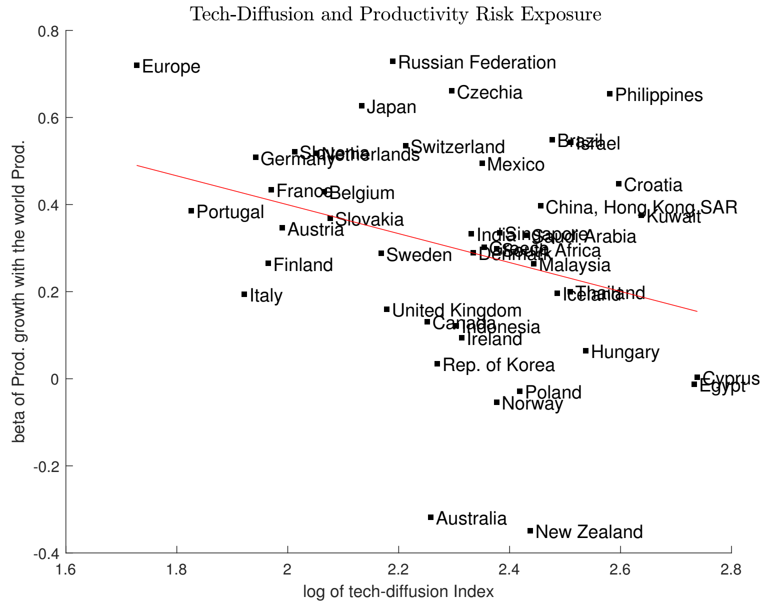
C Additional Figures

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



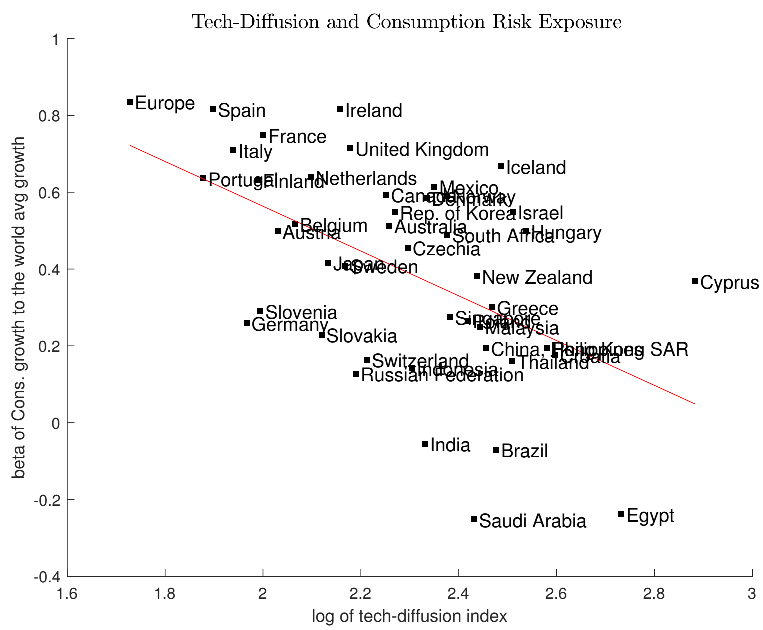
Notes: The graph shows the average tech-diffusion indices (FD) for our sample countries against their average excess returns (referred to as RX) and real interest rate differentials (relative to the U.S., referred to as RID). The left panel reports results for "All Countries", while the right panel shows 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 in each country.

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



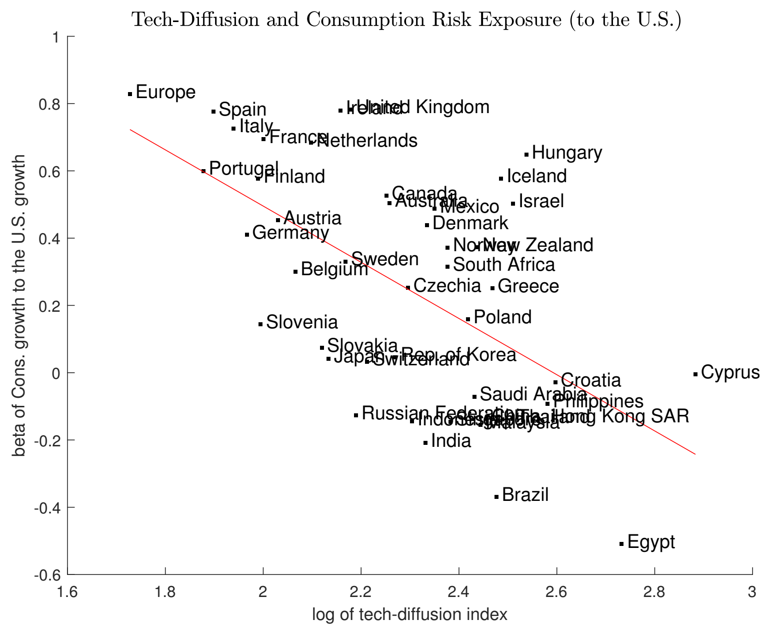
Notes: The figure shows the productivity growth betas against the average tech-diffusion measure (FD) for a broader set of countries. The construction of productivity growth betas is described under figure 2.

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



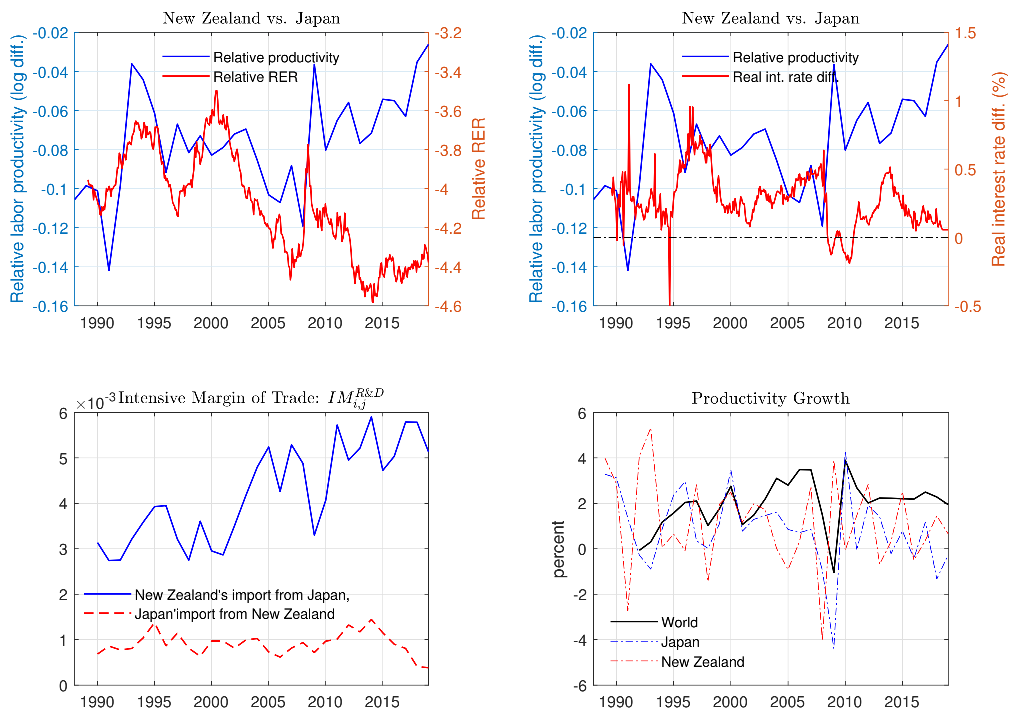
Notes: The figure shows the consumption growth betas against the average tech-diffusion measure (FD) for a broader set of countries. The construction of consumption growth betas is described under figure 2.

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



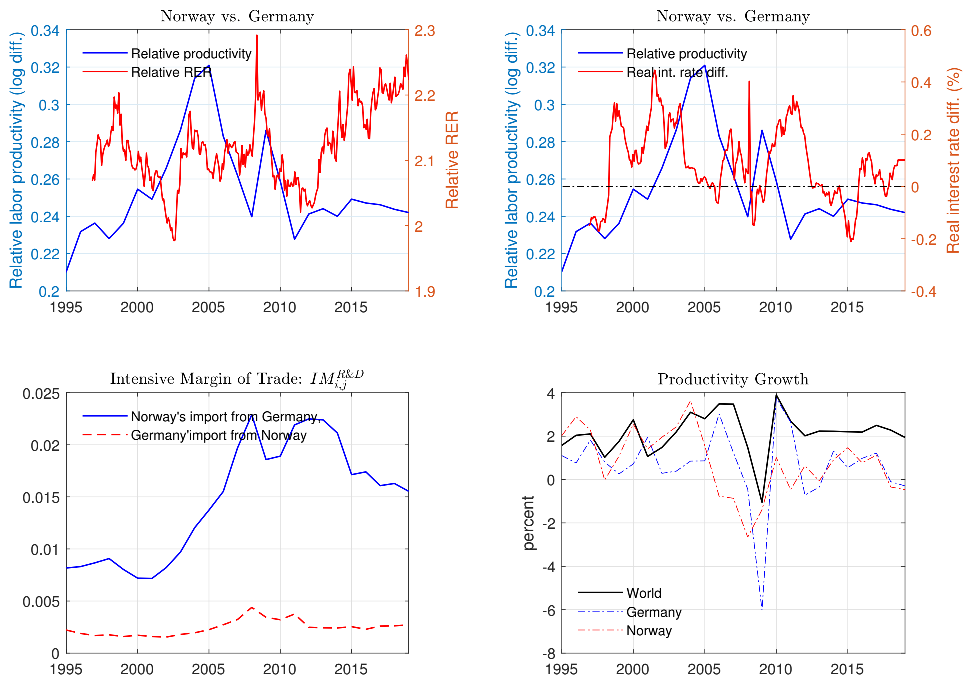
Notes: The figure shows the consumption risk exposure to the U.S. economy against the average tech-diffusion measures (FD). Each country's consumption risk exposure to the U.S. economy is calculated based on the following regression: $\Delta\text{Consumption}_{i,t} = \alpha_i + \beta_i^{c,US} \times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

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



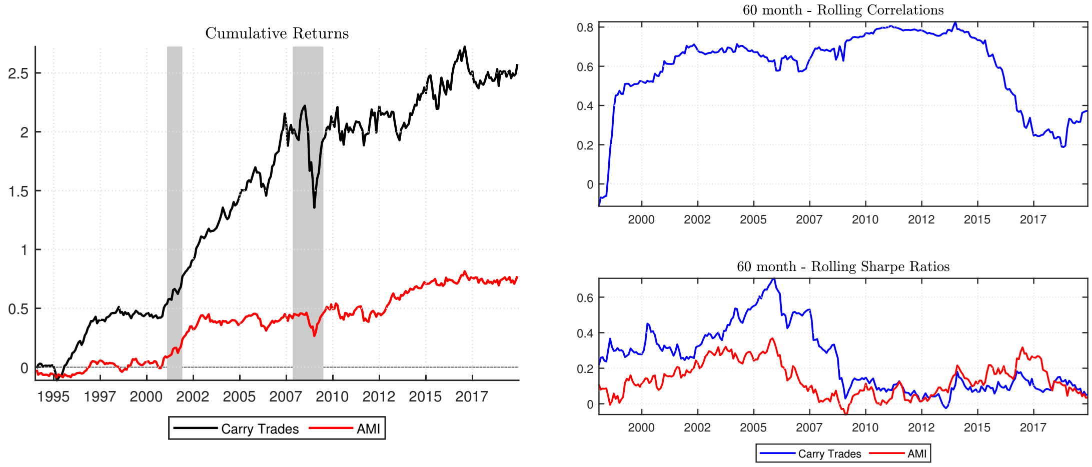
Notes: The figure shows the time series of productivities, the relative real exchange rates, real interest rate differentials, and R&D content of imports (intensive margin) for a pair of high and low-tech-diffusion countries. In the bottom left panel, the classification of high-technology goods is based 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 vs. 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

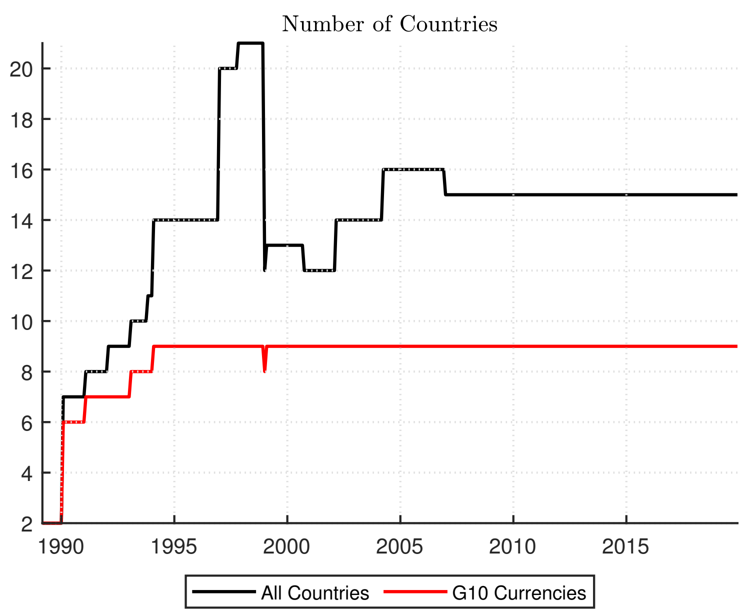
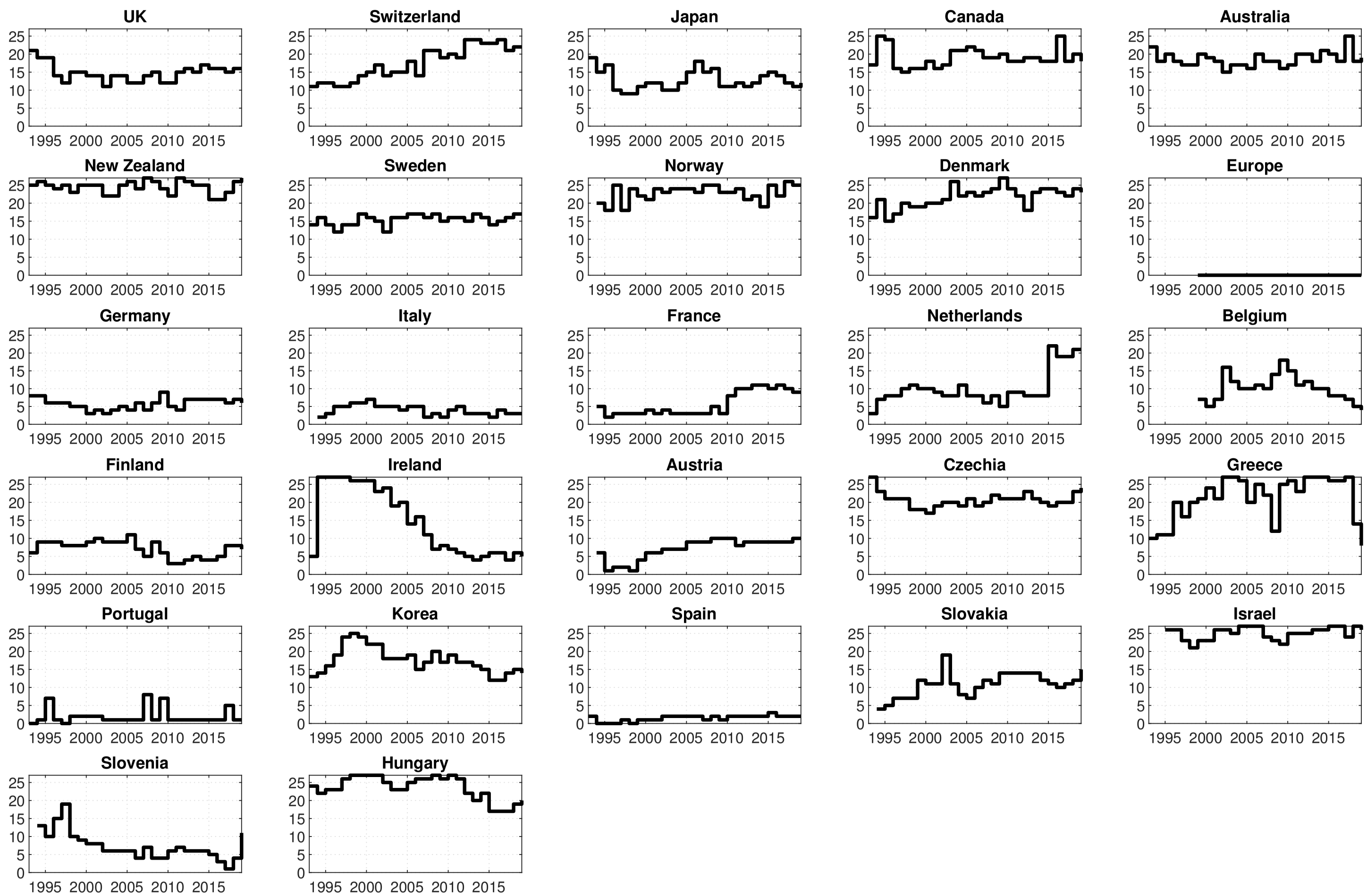
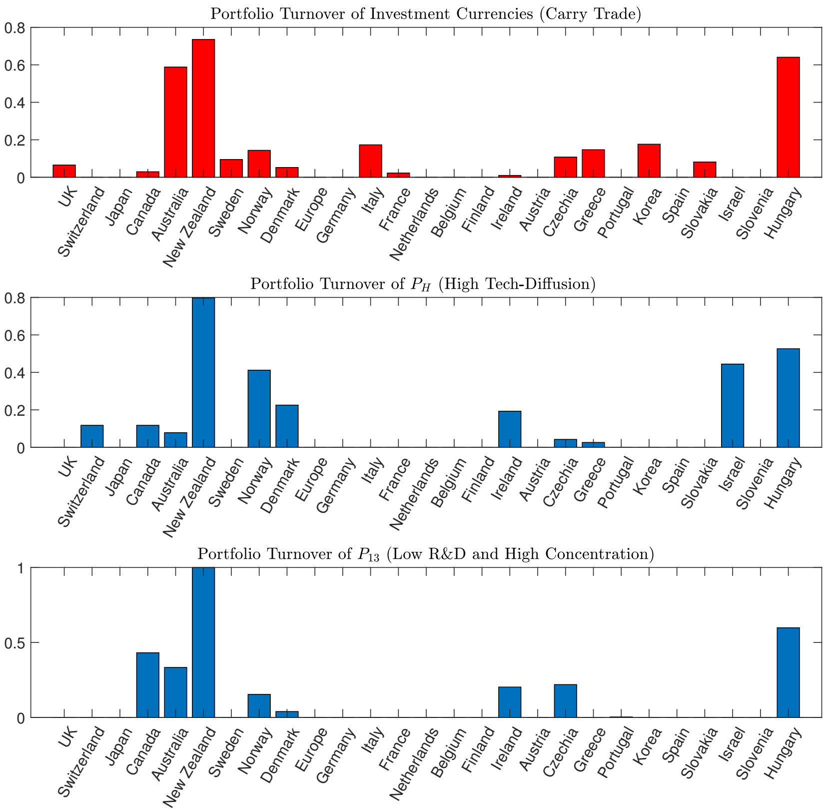


Figure C.9: Ranking of Technology Diffusion Measures (TD)



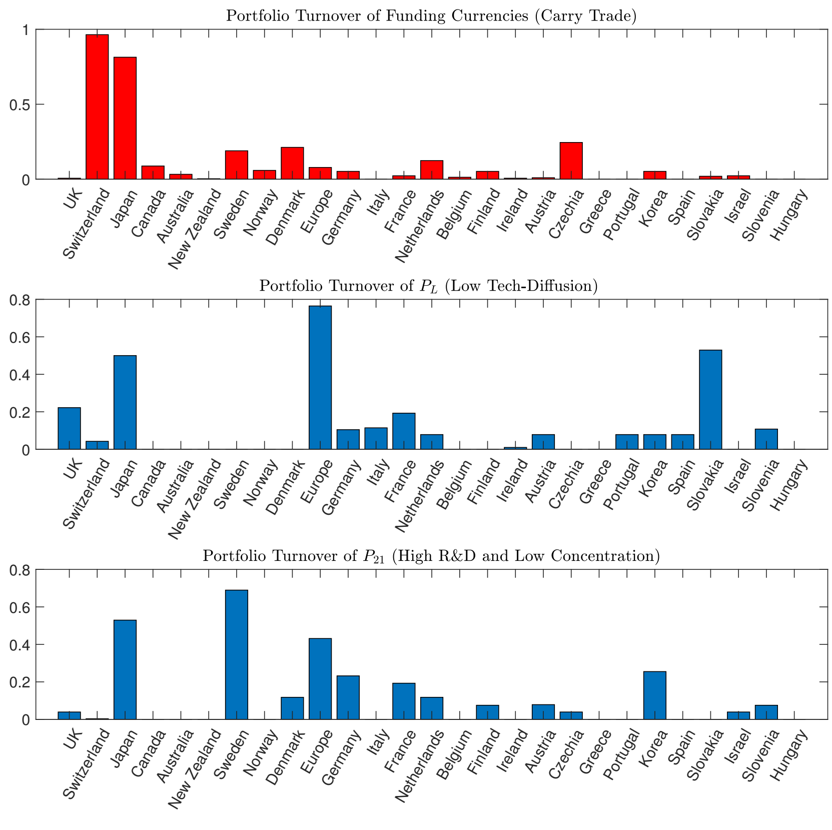
Notes: The figure displays the ranking of each country's tech-diffusion measure. Rankings are normalized each month to between 1 and 27, the maximum number of currencies in our sample. The data are collected from Datastream *via* Barclays and Reuters, which contain monthly series from January 1993 to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

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



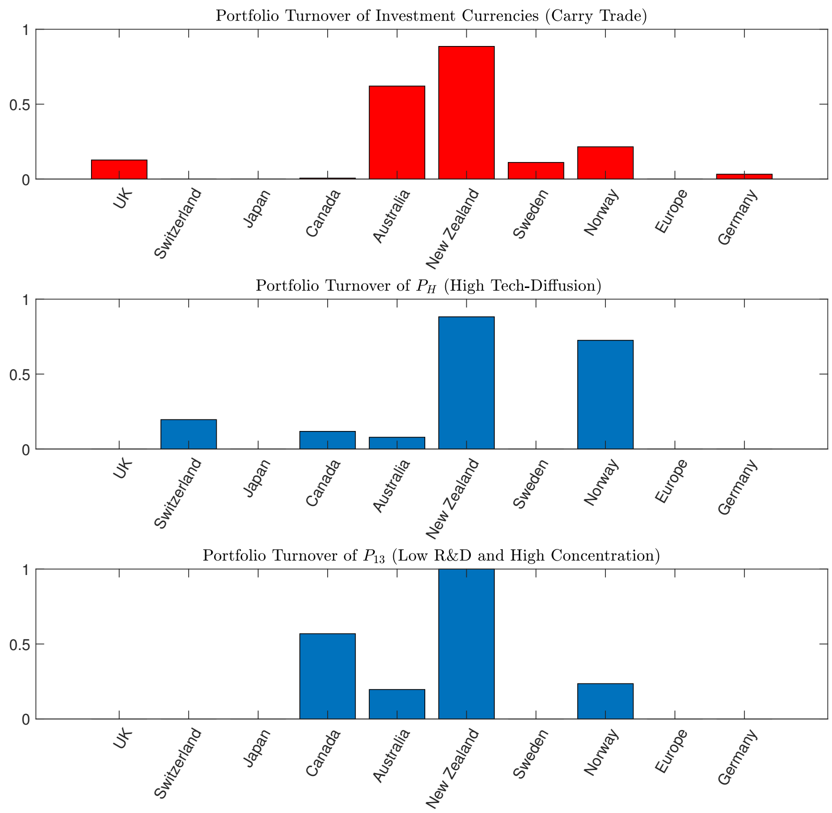
Notes: The figure displays turnover rates of the carry trade portfolio (upper panel), tech-diffusion-sorted portfolio (middle panel), and portfolio constructed by double-sorting strategy (bottom panel). The results are based on the sample of all countries. A larger number means that a country more frequently 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**)



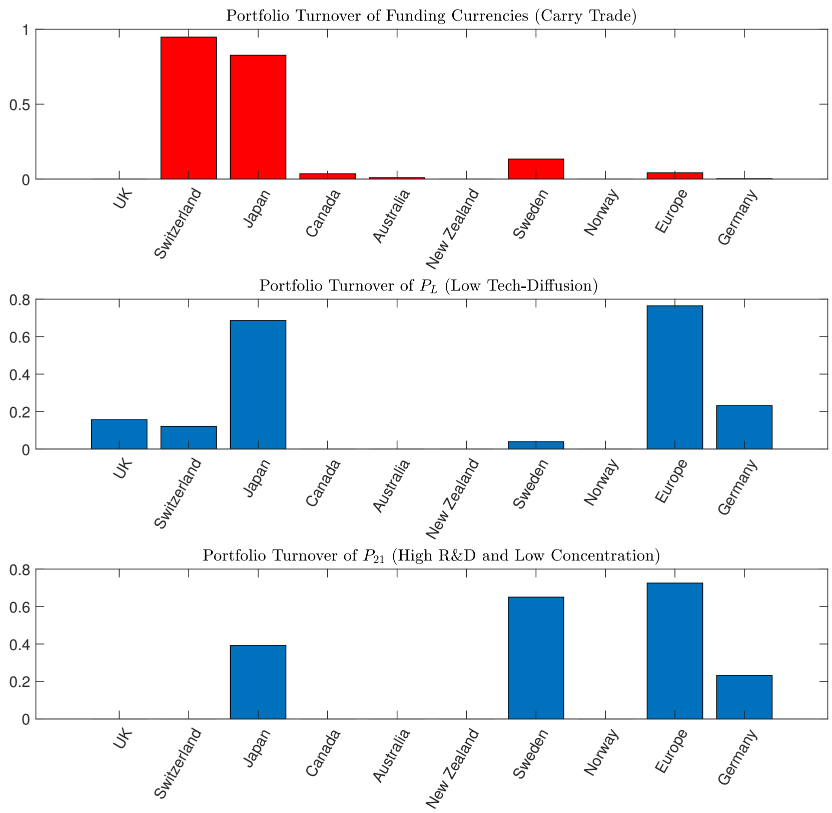
Notes: The figure displays turnover rates of the carry trade portfolio (upper panel), tech-diffusion-sorted portfolio (middle panel), and portfolio constructed by double-sorting strategy (bottom panel). The results are based on the sample of all countries. A larger number means that a country more frequently 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**)



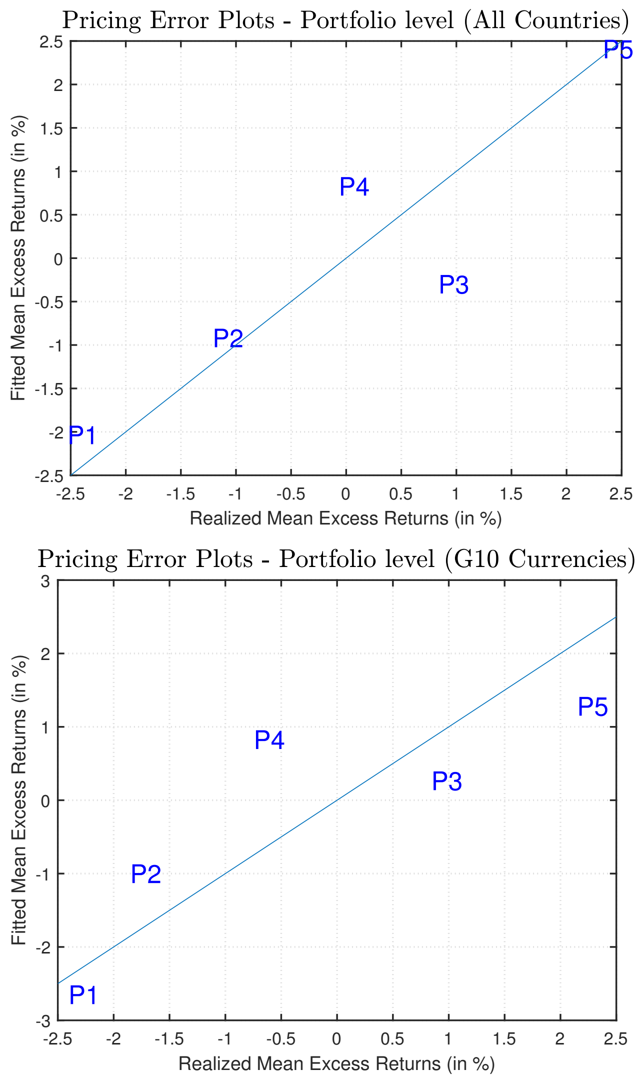
Notes: The figure displays turnover rates of the carry trade portfolio (upper panel), tech-diffusion-sorted portfolio (middle panel), and portfolio constructed by double-sorting strategy (bottom panel). The results are based on the sample of G10 currencies. A larger number means that a country more frequently 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**)



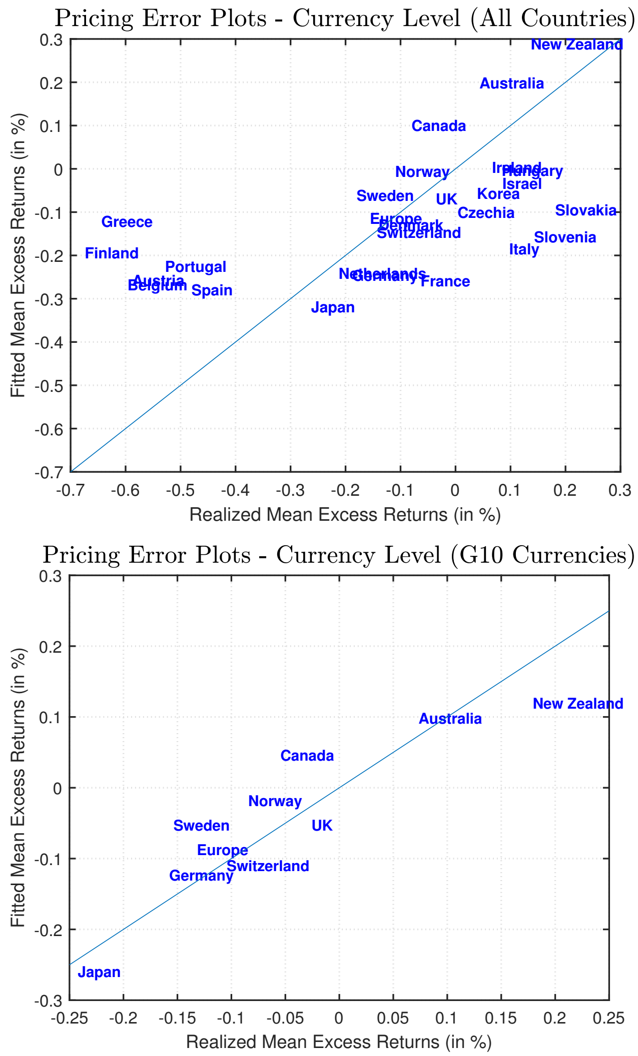
Notes: The figure displays turnover rates of the carry trade portfolio (upper panel), tech-diffusion-sorted portfolio (middle panel), and portfolio constructed by double-sorting strategy (bottom panel). The results are based on the sample of G10 currencies. A larger number means that a country more frequently 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

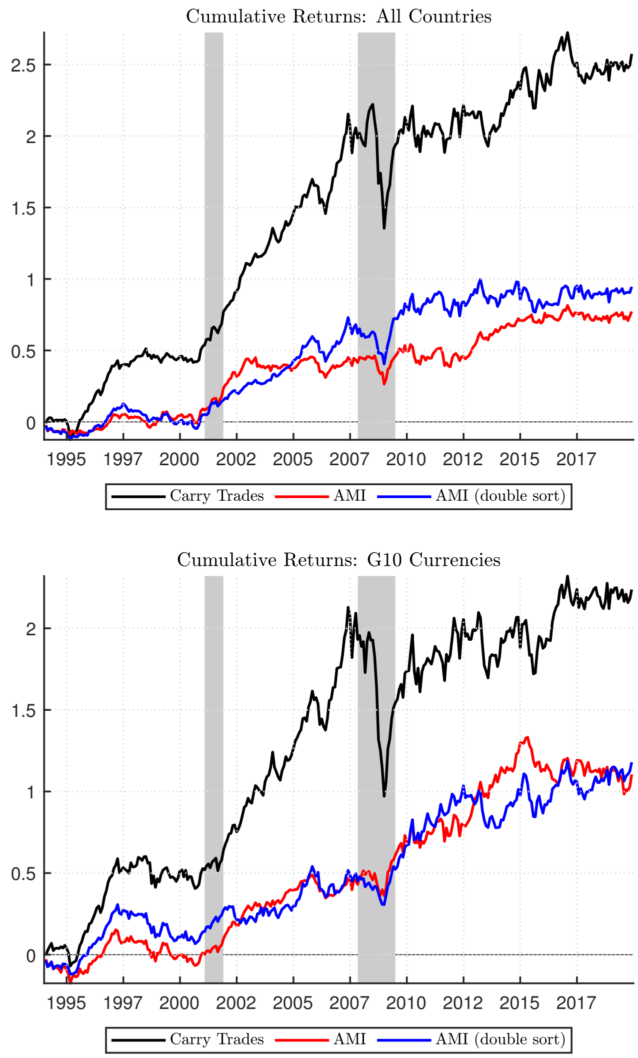


Notes: The figure plots the pricing errors for the currency-level asset pricing. First, we run a time-series regression of currency return $rx_{j,t}$ on DOL_t and AMI_t factors (with a constant). Then, we run the cross-sectional regression, period by period, to get the estimates of factor price: λ_{DOL} 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: Illustration of Double-Sorting Strategy

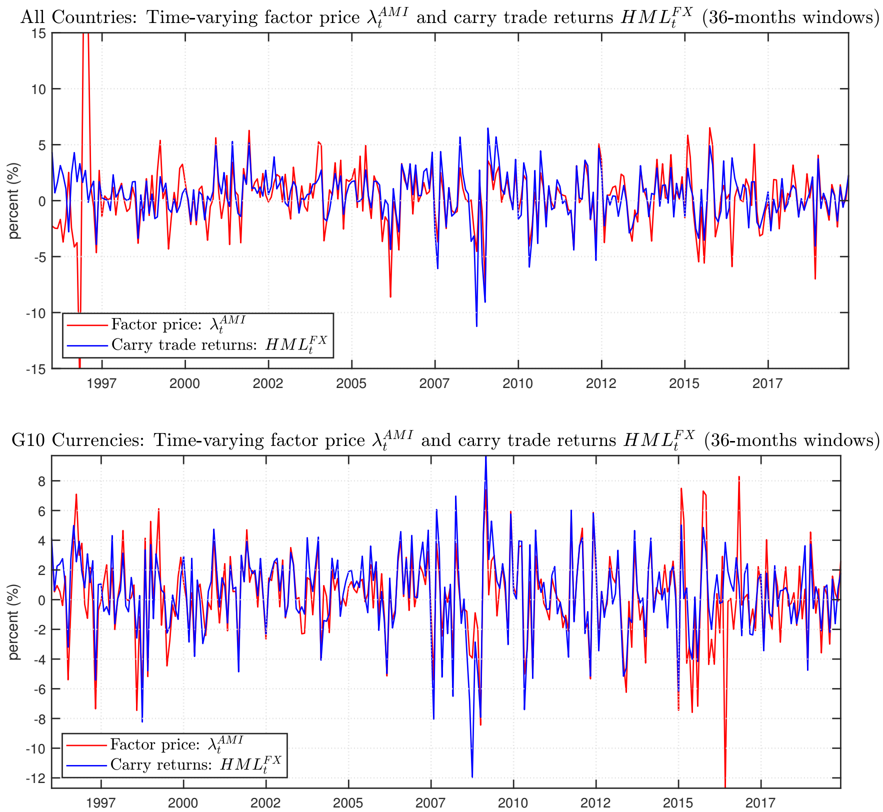
	low TC	medium TC	high TC
low *R&D*	P_{11} (10%)	P_{12} (10%)	P_{13} (20%)
high *R&D*	P_{21} (20%)	P_{22} (10%)	P_{23} (10%)

Figure C.17: Cumulative Returns: Double-Sorting Strategy



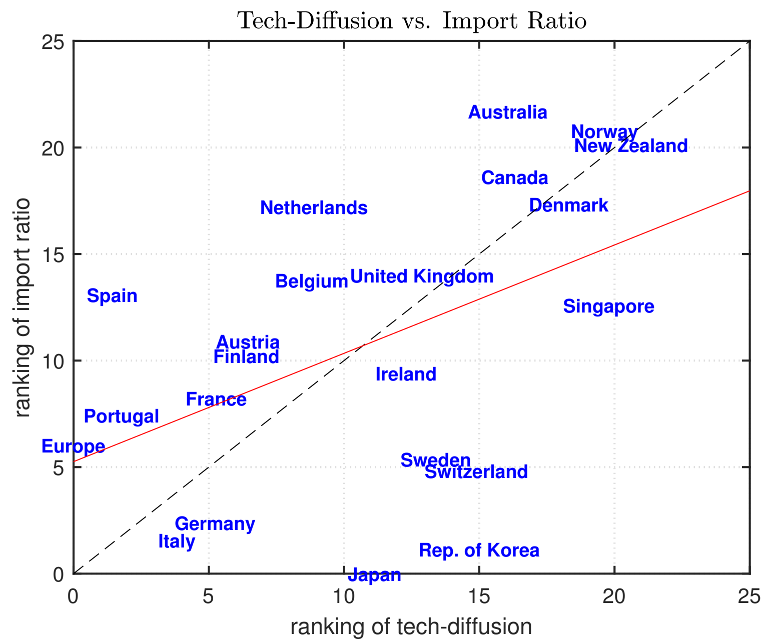
Notes: The figure compares the cumulative returns of tech-diffusion-sorted portfolio (AMI) and double-sort portfolio ($AMI^{2\times3}$). The upper panel shows the group of "All Countries", while the lower panel shows "G10 Currencies". The data contain monthly series from January 1993 to December 2019.

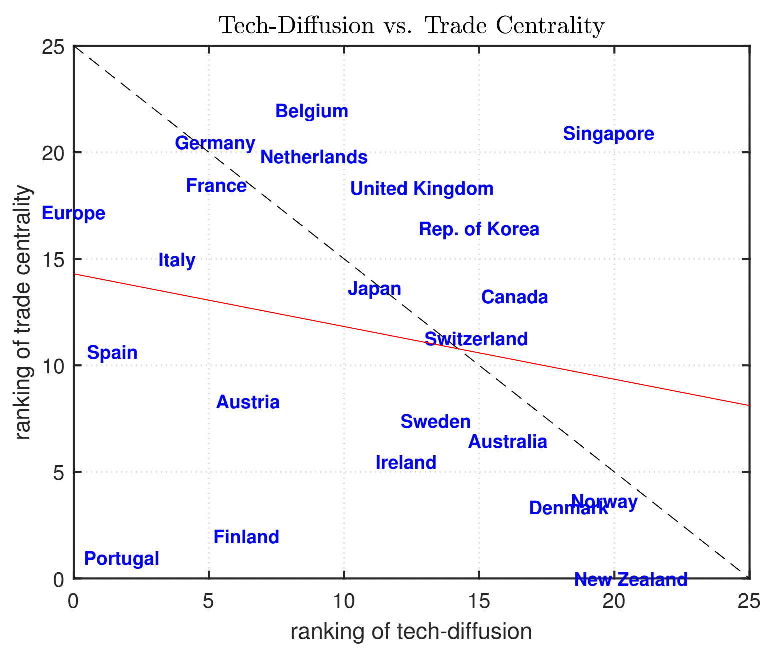
Figure C.18: Time-Varying Factor Prices: $\lambda_{AMI,t}$



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}).

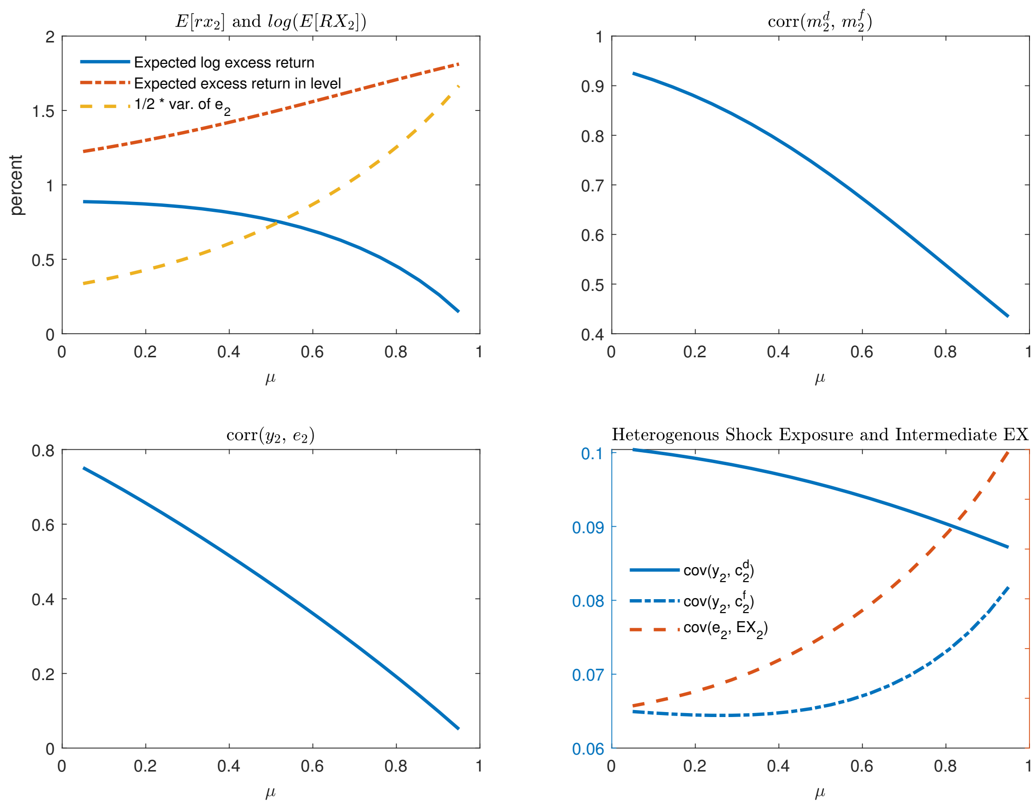
Figure C.19: Alternative Currency Risk Factors: Tech-Diffusion, Centrality, and Import Ratio





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: 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 $\rho_{df} = 0.4$.