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Mariana Sans
Cecilia Dassatti

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Mariana Sans[a*], Cecilia Dassatti[b**]

a *University of Maryland*
b *Banco Central del Uruguay*

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Resumen

Este trabajo analiza cómo cambios en el costo relativo de endeudarse en pesos frente al dólar pueden inducir una asignación ineficiente del capital. Un modelo teórico muestra que los costos de financiamiento heterogéneos —según la moneda de endeudamiento— pueden distorsionar la asignación incluso entre firmas con igual productividad. Usando datos de empresas uruguayas entre 2012 y 2019, encontramos que una mejora en las condiciones de financiamiento en moneda local —equivalente a una reducción de un desvío estándar en la paridad de tasas de interés ajustada por expectativas de tipo de cambio (UIP)— incrementa la ineficiencia en 11 puntos porcentuales en los tres años siguientes y en 4 puntos en el año contemporáneo. Este efecto se explica por un cambio hacia el endeudamiento en pesos, que se vuelve más barato y accesible para firmas pequeñas y menos productivas que no acceden al crédito en dólares.

Abstract

This paper analyzes how changes in the relative cost of borrowing in local versus foreign currency—captured by deviations from Uncovered Interest Parity—can lead to capital misallocation. A theoretical model shows that heterogeneous borrowing costs, stemming from currency denomination, can distort allocation even among equally productive firms. Using firm-level data from Uruguay (2012–2019), we find that a one standard deviation decline in this relative cost (i.e., a decrease in UIP deviations) increases misallocation by 11 percentage points over the following three years and by 4 points contemporaneously. This effect operates through a shift toward peso borrowing, which becomes cheaper and more accessible to small, less productive firms that are typically excluded from dollar credit markets.

JEL: F31, E44, O16
Keywords: Currency Mismatches; Misallocations; Financial frictions

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1 Introduction

Factor misallocation is a plausible explanation for the large and persistent differences in productivity and output per capita between emerging and advanced economies; work that was pioneered by Restuccia and Rogerson (2008) and Hsieh and Klenow (2009). In this paper, we employ a direct approach and investigate whether changes in the relative cost of borrowing in local versus foreign currency - captured by deviations from the Uncovered Interest Parity (UIP) condition - can lead to low aggregate productivity through misallocation.

In emerging markets, firms often borrow in dollars as well as in local currency. When the cost of peso borrowing falls relative to dollar borrowing (i.e., UIP deviations decrease), this generates heterogeneous borrowing costs that can lead to factor misallocation even if firms have the same productivity. This assumption is relaxed in the empirical analysis, where firm-level productivity differences play a central role in determining credit access.In emerging markets, firms often borrow in dollars as well as in local currency. When the cost of peso borrowing falls relative to dollar borrowing (i.e., UIP deviations decrease), this generates heterogeneous borrowing costs that can lead to factor misallocation even if firms have the same productivity. This assumption is relaxed in the empirical analysis, where firm-level productivity differences play a central role in determining credit access.

Empirically, we find that when peso borrowing becomes cheaper relative to the dollar, due to smaller deviations from the UIP, this is associated with substantial increases in capital misallocation. Using annual firm-level data from Uruguay spanning 2012–2019, a period characterized by increasing capital misallocation and declining UIP deviations, we find that a one standard deviation decline in the relative cost of peso borrowing (as captured by UIP deviations) leads to an increase of about 4 p.p. contemporaneously and a cumulative increase in capital misallocation of 11 p.p. in the subsequent three years—explaining much of the observed increase in misallocation during this period and the slowdown in aggregate TFP.

Next, we investigate the mechanisms through which these changes in relative borrowing costs can lead to capital misallocation. We focus on currency mismatches and dollar/peso borrowing as potential mechanisms: movements in UIP deviations alter the incentives of firms to borrow in different currencies based on their characteristics, affecting the degree of currency mismatch. With these mechanisms, we first try to explain the steady-state misallocation and then the dynamic misallocation.[1]

To do so, in our model we decompose the variance of $log(MRPK)$, our misallocation measure, into components of variance between and within based on the status of mismatch between firms. Since the only level of firm heterogeneity in the model is the currency in which firms borrow, and hence their currency mismatch (they all sell in pesos), total variance equals the between-variance component, which captures differences between matched and mismatched firms. We show that the between-component depends on the relative cost of borrowing in pesos versus dollars, captured by deviations from UIP. We also show that the between variance component is increasing in the working capital parameter, i.e., in the

[1] Steady state misallocation refers to the trend misallocation while dynamic misallocation to the cyclical variation in misallocation.

degree of financial frictions.

We derive the partial derivative of aggregate output with respect to the cost of dollar borrowing (that is, when the relative cost of peso borrowing declines) and find that its correlation with the degree of currency mismatch in the economy can be positive or negative depending on the initial direction of the UIP deviation. If the economy was initially in a stationary equilibrium with a UIP greater than one (in levels), moving to a new equilibrium with a lower UIP improves allocative efficiency and hence aggregate output. Most importantly, we show that the strength of this correlation depends on the working capital parameter. Previously, we showed that we can map the working capital parameter to the component V_b, so we conclude that V_b is a sufficient statistic to summarize the extent to which currency mismatches matter for steady-state misallocation and aggregate activity, something we can measure empirically.

In the data, we find that the between-variance component cannot explain more than 6% of total variance, suggesting that currency mismatches do not appear to be a major source of steady-state capital misallocation. Through the lens of our model, this finding implies that the degree of financial frictions, captured by the working capital parameter, is low. However, mismatch is not really a static concept; it can change over time with movements in relative borrowing costs. For this reason, we focus on what is moving alongside UIP deviations during this period to explain the observed dynamic misallocation. We find that it is the within variance component that accounts for it.

While the model assumes identical productivity across firms to isolate the role of financial frictions and currency mismatch, the empirical analysis acknowledges that productivity differs across firms in practice. This heterogeneity becomes particularly relevant in periods of declining relative peso borrowing costs, when small and less productive firms gain access to local currency credit. Although our model does not explicitly account for this selection mechanism, the evidence is consistent with its central logic: that segmentation in credit access—driven by currency-based borrowing frictions—distorts allocation, even more so when firms differ in fundamentals.

Further empirical analysis suggests that the observed dynamic misallocation is related to firms adjusting their borrowing currency depending on the relative cost of funding—i.e., switching from local currency to the dollar when dollar borrowing becomes more attractive, and from the dollar to pesos when peso borrowing becomes cheaper. Dollar borrowing is more selective: only large and productive firms can borrow in this currency, as also shown in Salomao and Varela (2022). When UIP deviations go down and peso borrowing becomes more accessible, small and less productive firms—those typically excluded from dollar credit—gain access to peso financing. These firms are unable to borrow in dollars in the first place, but they can borrow in pesos when it becomes cheap enough. In this way, lower UIP deviations enable "bad types" to access financing, directly increasing misallocation.

This dynamic may also be shaped by structural differences in the banking sector. In Uruguay, for instance, the peso credit market is more concentrated and potentially less competitive than the dollar market, where firms may have access to international lenders or export-linked financing (Mello, 2007; Gómez and Ponce, 2014; Mello and Ponce, 2022). As a result, the relative cost of borrowing in pesos may reflect not only macroeconomic risks or firm-level fundamentals but also credit market segmentation that enables banks to exert market power over firms without access to the dollar segment. This lack of competition in peso lending may amplify the selective access channel we identify, further contributing to the observed patterns of capital misallocation.

Contribution to the literature. The main contribution of this paper is to bring together the literature on misallocation and productivity with the literature on UIP deviations and currency mismatches.

The literature on misallocation, pioneered by Restuccia and Rogerson (2008) and Hsieh and Klenow (2009), shows how reduced-form wedges that generate dispersion of marginal revenue products across firms can lower aggregate TFP. This literature is mostly static. More recent work has endogenized these wedges using financial frictions and introduced dynamics such as Buera et al. (2011), Midrigan and Xu (2014), Moll (2014) and Bau and Matray (2023). In particular, this research project relates capital misallocation at the micro-level to firm-level financial decisions and to the aggregate implications of financial frictions, but in an open economy setting, so it is closest to Gopinath et al. (2017), Finlay (2022), and Andreasen et al. (2023).

Gopinath et al. (2017) document that during the 2000s, southern European countries experienced low productivity growth. To explain this, they develop a model with infinitely-lived firms and monopolistic competition in partial equilibrium with productivity shocks and capital adjustment costs, combined with a size-dependent borrowing constraint. They show that capital inflows, triggered by the lower interest rates, were misallocated towards high-net-worth firms that were not necessarily the most productive. Finlay (2022) develops a model with infinitely-lived firms in which exporters are more credit constrained than non exporters. He shows that tightening credit constraints for exporters lowers aggregate productivity because they are more productive. Andreasen et al. (2023) study the effects of capital controls on misallocation, exports and welfare with a dynamic Melitz-OLG model with heterogeneous firms, monopolistic competition, endogenous trade participation, and collateral constraints. Capital controls enter as a tax on foreign borrowing that increases the interest rate on debt and thus adds to the financial frictions already present because of the collateral constraint. They study the static, dynamic, and GE effects on misallocation by adding capital controls to this economy. The static effects are negative by the standard mechanism: financial constraints tighten the firms' access to credit, which reduces their capital and capital-labor ratios, and increases their prices, increasing their marginal revenue products. The dynamic effects are positive because financial constraints generate incentives for faster growth. GE effects that result from changes in aggregate variables are theoretically ambiguous. They tested the model using data on manufacturing firms during the 1990s Chilean capital control episode (the unremunerated reserve requirement, or encaje).

The novelty of our project is to study the role of deviations from UIP and currency mismatches as a source of misallocation. Mismatches play a similar role as capital controls in Andreasen et al. (2023), in the sense that they generate heterogeneity in the borrowing cost of firms. However, the role of currency mismatches gets "activated" depending on the direction of UIP deviations, the degree of financial friction and the characteristics of the firms.

With respect to the literature on UIP deviations and currency mismatches, this article is related to recent work showing that firms in emerging markets often borrow in US dollars because it is cheaper (Gutierrez et al. (2023), Keller (2021), Bocola and Lorenzoni (2020)). However, exposure to currency risk is heterogeneous. Adler et al. (2020) show that among the firms that borrow in dollars, exporters are naturally hedged while non-exporters that do not use FX hedging instruments are exposed to currency risk. Aguiar (2005), Kalemli-Özcan et al. (2016), Bleakley and Cowan (2008), Rodnyansky (2019) and Kalemli-Özcan et al. (2021) among others, show that the impact of exchange rate fluctuations on different firm-level decisions depends on their trade status, exposure to short-term dollar debt, dependence on imported inputs, and whether it is a depreciation or an appreciation shock. In this paper, we focus on the impact of currency mismatches and dollar/peso borrowing on misallocation.

Closest to this paper is Salomao and Varela (2022) that links currency mismatches with productivity. They propose that the choice of currency-debt composition of firms arises from a dynamic trade-off between exposure to currency risk and growth, given UIP deviations. At an extensive margin, only productive firms can tolerate the risk of the exchange rate and borrow dollars. At an intensive margin, productive firms with high return-to-investment employ this financing relatively more. Our paper also characterizes mismatched firms and finds similar results in terms of productivity and size. However, the contribution of our paper is to connect the features of firm sorting into dollar/peso borrowing given UIP deviations, with capital misallocation, which to the best of our knowledge has not been explored yet.

Structure of the paper. The remainder of the paper is structured as follows. Section 2 develops a theoretical model. Section 3 describes the data used in this paper. Section 4 presents the macroeconomic and financial background of Uruguay for the period under study. Section 5 reports empirical findings, while section 6 dissects the results, both theoretically and empirically. The last section concludes.

2 Model

2.1 Model environment

Objective. Propose a theory linking changes in the relative cost of borrowing in local versus foreign currency - captured by deviations from Uncovered Interest Parity (UIP) - to resource misallocation and, consequently, to aggregate productivity and activity. The focus is on firms with the same productivity that borrow in different currencies. The model is based on Hsieh and Klenow (2009), but employs a direct approach to generate capital wedges through standard financial friction and the introduction of dollar and peso borrowing. We use this framework to analyze the data.

To focus purely on the role of financial friction and differences in the relative cost of borrowing in pesos versus dollars, we assume that all firms have identical productivity. This simplification isolates the effect of currency denomination on capital wedges and misallocation.

Although empirical analysis incorporates firm-level productivity differences, important for understanding access to credit, this assumption allows the model to identify the distortions driven specifically by currency segmentation in financing.

Setup. Time is discrete, denoted by t, and continues infinitely. The economy is populated by firms and a representative household. The household is standard: consumes the final good, supplies labor, rents capital, and lends to firms. Households are endowed with capital that does not depreciate. In the firm sector, the final consumption good producer purchases inputs from monopolistically competitive intermediate input producers. Among these intermediate producers, some firms are mismatched (dollar borrowers) while others are matched (peso borrowers). In the model section, we use mismatched (matched) and dollar borrowers (peso borrowers) interchangeably. All firms sell in pesos.

Final good producer. The production function for the final consumption good is CES and is given by:

$$Y_t = \Big(\int_0^1 y_{it}^{\frac{\sigma-1}{\sigma}} di \Big)^{\frac{\sigma}{\sigma-1}} \tag{1}$$

where y_{it} is the intermediate input purchased from producer i and σ is the substitution elasticity between different inputs.

The optimality condition is given by:

$$p_{it} = Y_t^{\frac{1}{\sigma}} y_{it}^{-\frac{1}{\sigma}} \tag{2}$$

which gives the demand function for intermediate producers. p_{it} denotes the relative price of good i in terms of the final good, which serves as a numeraire.

Intermediate producers. A continuum of size one of firms produces intermediate goods. Within the continuum, there are two types of firms, $j \in \{mm, m\}$. Firms with $j = mm$ are mismatched, while $j = m$ denotes firms that are matched. The measure of the type$-mm$ firms is γ. All intermediate producers have a CRS production function given by:

$$y_{it}^j = A(k_{it}^j)^{\alpha}(n_{it}^j)^{1-\alpha} \tag{3}$$

where $\alpha \in (0, 1)$ is the capital share in production and A is the total factor productivity (TFP), which is constant over time and is not firm-specific. Firms rent capital (k_{it}^j) and hire labor (n_{it}^j) from competitive markets and pay factor prices R_t^k and W_t, respectively. All intermediate producers sell domestically in pesos at a price p_{it}.

Firms face an intratemporal working capital constraint and a borrowing constraint; in the spirit of Mendoza (2010):

$$L_{it}^j = \psi R_t^k k_{it}^j \tag{4}$$

$$R_t^{b,j} \psi L_{it}^j \leq \theta R_t^k k_{it}^j \tag{5}$$

The working capital constraint (equation 4) can be rationalized through firms' need to finance in advance a fraction ψ of their capital working needs; L^j_{it} denotes the total working capital needs. The borrowing restriction (equation 5) establishes that firms can borrow up to a fraction θ of their collateral $R^k_t k^j_{it}$. Note that the borrowing constraint boils down to the following parameter restriction: $R^{b,j}_t \leq \frac{\theta}{\psi}$, which we make sure is satisfied in the model calibration.

Mismatched firms borrow in dollars, at the peso-converted rate $R^{b*}_t = s_t(1+r^*_t)$, where r^*_t denotes the dollar loan rate and s_t denotes the nominal exchange rate. Matched firms borrow in pesos at rate $R^b_t = 1 + r_t$. We assume that r_t, r^*_t, and s_t are given.

The per-period profits in nominal pesos of firms are given by:

$$\pi^j_{it} = p^j_{it} y^j_{it} - R^{b,j}_t \psi R^k_t k^j_{it} - (1-\psi) R^k_t k^j_{it} - W_t n^j_{it} \tag{6}$$

In summary, the problem of the firm i is to maximize the profits per period 6 subject to 2, 3, 4 and 5. Firms choose $\{n^j_{it}, k^j_{it}, p^j_{it}\}$.

The optimality conditions for their inputs:

$$MRPL^{mm}_{it} \equiv \frac{\sigma-1}{\sigma}(1-\alpha)\frac{p^{mm}_{it} y^{mm}_{it}}{n^{mm}_{it}} = W_t \tag{7}$$

$$MRPL^{m}_{it} \equiv \frac{\sigma-1}{\sigma}(1-\alpha)\frac{p^{m}_{it} y^{m}_{it}}{n^{m}_{it}} = W_t \tag{8}$$

$$MRPK^{mm}_{it} \equiv \frac{\sigma-1}{\sigma}\alpha\frac{p^{mm}_{it} y^{mm}_{it}}{k^{mm}_{it}} = R^k_t\left(1-\psi+\psi R^{b*}_t\right) \tag{9}$$

$$MRPK^{m}_{it} \equiv \frac{\sigma-1}{\sigma}\alpha\frac{p^{m}_{it} y^{m}_{it}}{k^{m}_{it}} = R^k_t\left(1-\psi+\psi R^{b}_t\right) \tag{10}$$

Equations 7 and 8 are the marginal revenue products of labor (MRPLs) of mismatched and matched firms, respectively, while 9 and 10 are their marginal revenue products of capital (MRPKs). MRPLs are equalized between firms since they face the same factor prices and no distortions, but this is not necessarily the case for MRPKs. MRPKs will be equalized across firms when they face the same distortions, which occur when the borrowing costs in the two currencies are equalized. The dispersion in marginal revenue products is indicative of misallocation as established by Hsieh and Klenow (2009).

Optimal prices are given by a common markup over their marginal cost for each j-type:

$$p^j_{it} = \frac{\sigma}{\sigma-1}\left(\frac{MRPL_t}{1-\alpha}\right)^{1-\alpha}\left(\frac{MRPK^j_{it}}{\alpha}\right)^{\alpha}\frac{1}{A} \tag{11}$$

Market clearing. Aggregating across firms i and j-types gives:

$$Y_t = \left(\int_0^1 y_{it}^{\frac{\sigma-1}{\sigma}}\, di\right)^{\frac{\sigma}{\sigma-1}} = \left(\gamma (y^{mm}_{it})^{\frac{\sigma-1}{\sigma}} + (1-\gamma)(y^{m}_{it})^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} \tag{12}$$

$$N_t = \gamma n^{mm}_{it} + (1-\gamma) n^{m}_{it} \tag{13}$$

$$K_t = \gamma k^{mm}_{it} + (1-\gamma) k^{m}_{it} \tag{14}$$

where capital letters denote aggregate level variables.

2.2 Main results

Aggregation and stationary equilibrium. Now we turn to the aggregate economy to understand how changes in the relative cost of borrowing in local versus foreign currency—captured by deviations from Uncovered Interest Parity (UIP)—can impact aggregate activity. Given our focus on misallocation, we restrict our attention to a stationary equilibrium in which all aggregate variables remain constant over time. We derive aggregate output Y in terms of factor prices, aggregate inputs (K, N), and the capital wedge distribution, as follows:

$$Y = \hat{A} K^{\alpha} N^{1-\alpha}, \text{ where} \tag{15}$$

$$\hat{A} = TFP = \frac{\left\{ \int_0^1 \left(\frac{A}{MRPK_i^{\alpha}} \right)^{\sigma-1} di \right\}^{\frac{1+\alpha\sigma-\alpha}{\sigma-1}}}{\left\{ \int_0^1 \frac{A^{\sigma-1}}{MRPK_i^{1+\alpha\sigma-\alpha}} di \right\}^{\alpha}} \tag{16}$$

where $MRPK_i$'s follow optimality conditions 9 and 10, and $\hat{A}$ is aggregate TFP.

Assuming $MRPK_i$ follows a log-normal distribution with mean $\mathbb{E}(logMRPK_i)$ and variance $\mathbb{V}(logMRPK_i)$, we can derive a closed-form expression for aggregate $logTFP$ as follows:

$$logTFP = logA - \frac{\alpha(1+\alpha\sigma-\alpha)}{2} \mathbb{V}(logMRPK_i) \tag{17}$$

Expression 17 reveals a direct connection between the micro-level wedges, namely the financial frictions and currency mismatches, summarized by $\mathbb{V}(logMRPK_i)$, and aggregate TFP. Aggregate productivity is a decreasing function of $\mathbb{V}(logMRPK_i)$, with the magnitude of the effect depending on the elasticity of substitution σ and the capital cost share α. When σ is high, goods are more substitutable (i.e., we are closer to perfect competition), and misallocation becomes particularly costly. The higher α, the more firms rely on capital as input, but since capital rental faces a wedge, the more severe the losses from misallocation will be. Aggregate TFP increases monotonically in A, the general productivity of firms. The fact that the dispersion in the average product of capital maps directly into TFP losses from financial frictions and currency mismatches reflects our stark assumption that there are no other sources of variation in the average products of capital.

We are interested in the contribution of changes in $\mathbb{V}(logMRPK_i)$ in $log(TFP)$, hence in the following object:

$$dlogTFP = -\frac{\alpha(1+\alpha\sigma-\alpha)}{2} \mathbb{V}(logMRPK_i) \tag{18}$$

We next study how much of the changes in misallocation are driven by changes in UIP.

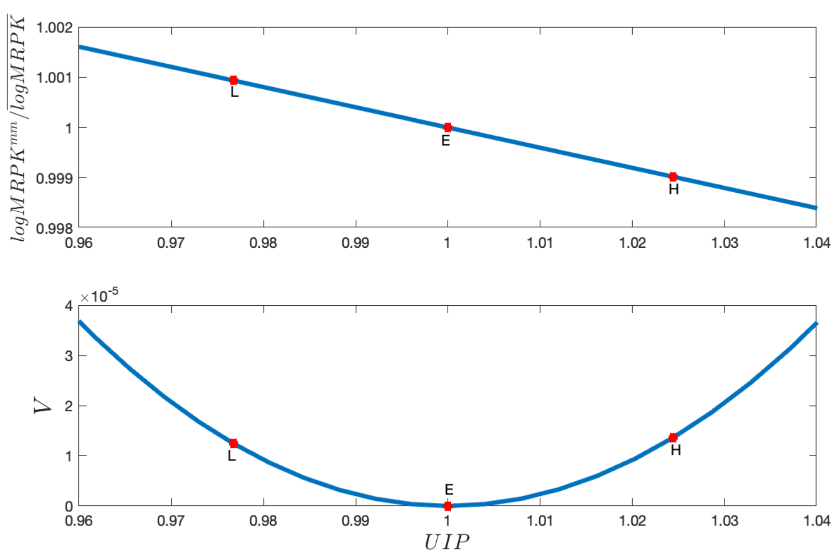
Relative Borrowing Costs (UIP Deviations) and Capital Misallocation. The first observation is that $\mathbb{V}(logMRPK_i)$ depends on the relative cost of borrowing in pesos versus the dollar. We focus on deviations from the Uncovered Interest Parity (UIP) to capture heterogeneous borrowing costs, where:

$$UIP = \frac{R_i^b}{R_i^{b*}} = \frac{1+r}{s_t(1+r^*)} \tag{19}$$

UIP is defined as excess returns on peso assets such that $UIP < 1$ ($UIP > 1$) implies that borrowing in dollars is more (less) expensive than borrowing in pesos. When $UIP = 1$ the cost of borrowing in the two currencies is equalized.

In Figure 1 we illustrate this result numerically. We plot the between variance $\mathbb{V}$ for different levels of UIP deviations in the bottom panel, and the ratio between the marginal revenue product of the mismatched firms to that of the average ($\frac{logMRPK^{mm}}{\overline{logMRPK}}$) in the top panel to capture how mismatched firms perform relative to the average firm. We show that when $UIP = 1$ marginal revenue products of capital are equalized, hence $\mathbb{V} = 0$ and $\frac{logMRPK^{mm}}{\overline{logMRPK}} = 1$. UIP deviations produce dispersion in marginal revenue products; hence $\mathbb{V}$ becomes positive and $\frac{logMRPK^{mm}}{\overline{logMRPK}}$ becomes different from 1. In Proposition 1 we summarize the key takeaways from this first observation.

Figure 1: MRPK dispersion, between variance, and UIP deviations



Note: $logMRPK^{mm}$ is the $logMRPK$ of mismatched firms and $\overline{logMRPK}$ is the average $logMRPK$. $\mathbb{V}$ is the between variance computed as in 25. Calibration: $\psi = 0.25$ as in Mendoza (2010), $\theta = 0.8$, $R^k = 100$, and $\gamma = 0.4$ to match the average Uruguayan data for the period under study.

Proposition 1: given the model assumptions, if the initial allocation is:

1. *Efficient (E: $UIP = 1$), that is, the borrowing costs in the two currencies is equalized, hence $\frac{logMRPK^{mm}}{\overline{logMRPK}} = 1$. Any movement in the exchange rate will generate misallocation, i.e., $\mathbb{V} > 0$.*

2. *Inefficient (L: $UIP < 1$), that is, dollar borrowing is more expensive, hence $\frac{logMRPK^{mm}}{logMRPK} > 1$. Increases in UIP will improve allocative efficiency ($\mathbb{V}$ declines) until it reaches its efficient level at $UIP = 1$.*

3. *Inefficient (H: $UIP > 1$), that is, dollar borrowing is cheaper. Increases in UIP will worsen allocative efficiency ($\mathbb{V} >> 0$) because $\frac{logMRPK^{mm}}{logMRPK} << 1$.*

Proposition 1 shows that UIP deviations play a similar role as capital controls in Andreasen et al. (2023) in the sense that they generate heterogeneity in the borrowing cost of firms. However, the role of currency mismatches gets "activated" with UIP deviations, given the financial constraints. We will use this framework to analyze the data.

3 Data

We use the merged credit registry and corporate financial statements of Uruguay, a representative small open emerging market, for the period 2012-2019. Data are from the Central Bank of Uruguay (BCU). In Appendix A.1 we provide full details on the data and how we clean it.

From the Annual Economic Activity Survey (*Encuesta Anual de Actividad Económica*) we use the annual balance sheet and income statements of the firms, which include the currency decomposition. The survey is compiled by the National Institute of Statistics (INE) in collaboration with the BCU.[2] It is representative of the universe of Uruguayan firms that have 10 or more employees. As per INE's classification, the set of firms with more than 10 employees includes a portion of small firms (those with 5-19 employees) and the universe of medium (those with 20-99 employees) and big firms (more than 100 employees). All big firms are surveyed every year, and it is a rotating panel for small and medium firms. Small and medium firms are randomly sampled and remain in the sample for at least three years, and when replaced, firms with similar characteristics (size and sector) take their spot. Construction, agriculture, and the public sector, which together represent less than 20% of GDP, are excluded from the survey.

The BCU compiles and manages the credit registry of firms, which is a monthly record of all loans granted in the financial sector to firms. It reports the outstanding stocks at the end of the month and includes, among others, the borrower's id, industry, loan amount, currency, maturity, loan type, guarantee type and amount, and the borrower's credit rating.[3]

We further augment this dataset with macroeconomic and financial data from different sources. From the BCU, we get investment and industry-specific deflators. From the IMF-IFS we get the spot exchange rate and GDP data. The exchange rate is defined as pesos per dollar, so an increase in the exchange rate is a depreciation. From FRED and the Uruguay Electronic Securities Exchange of Uruguay (*BEVSA*) we get interest rate data, and from

[2]The data is collected for statistical purposes and informs the National Accounts the Central Bank produces.

[3]The database includes only banks and a cooperative of savings and credit that acts as a retail bank and is also subject to bank regulation.

Consensus Economics we get expected exchange rates. Finally, from the Penn World Table version 10.01 (Feenstra et al. (2015)) we get data for aggregate TFP.

4 Macroeconomic and financial background

In this section we provide the macroeconomic and financial context of Uruguay for the period under study (2012-2019). We highlight four facts: i) a slowdown of economic activity and TFP growth, ii) positive but declining UIP deviations, iii) high corporate currency mismatches, and iv) the prevalence of financial frictions.

Since its recovery from the 2002 financial crisis and through 2011, Uruguay has experienced a period of high economic growth; led by important structural reforms and favorable international conditions (low international interest rates, large capital inflows (FDI), and high agricultural commodity prices). GDP growth was as high as 7.8% in 2010, but started to slow down in subsequent years. It stopped growing in mid-2018, reaching a modest 0.35% in 2019; accompanying the slowdown in the global economy and of its main trading partners. The growth of TFP also followed the slowdown in GDP (Figure 2).

During this period, dollar borrowing was cheaper, captured by positive UIP deviations. We compute UIP deviations or expected excess returns in logs as:

$$UIP_{t+h} \equiv \text{exret}^e_{t+h} = \underbrace{(r_t^{pesos} - r_t^{USD})}_{\text{IR differential}} - \underbrace{(s^e_{t+h} - s_t)}_{\text{ER adjustment}} \tag{20}$$

where r_t and r_t^{USD} are the 12-month Uruguayan and US government bond rates, while s_t is the spot exchange rate in units of pesos per USD, and s^e_{t+h} is the expected exchange rate a $h = 12$-months ahead.[4]

Positive UIP deviations during this period were driven by interest rate (IR) differentials that were higher than expected depreciations (ER adjustment), as shown in Figure 2.[5] Although it was always cheaper to borrow in dollars during this period, UIP deviations were mostly decreasing, meaning that peso borrowing became more accessible over time, in relative terms.

Consistent with the observed positive UIP deviations, dollar borrowing among firms was high during this period, as shown in Table 1. If we look at dollar borrowing by export status, which is a proxy of the currency in which firms invoice, we find that 63% of non-exporters borrowed in dollars, while 80% of exporters do so.

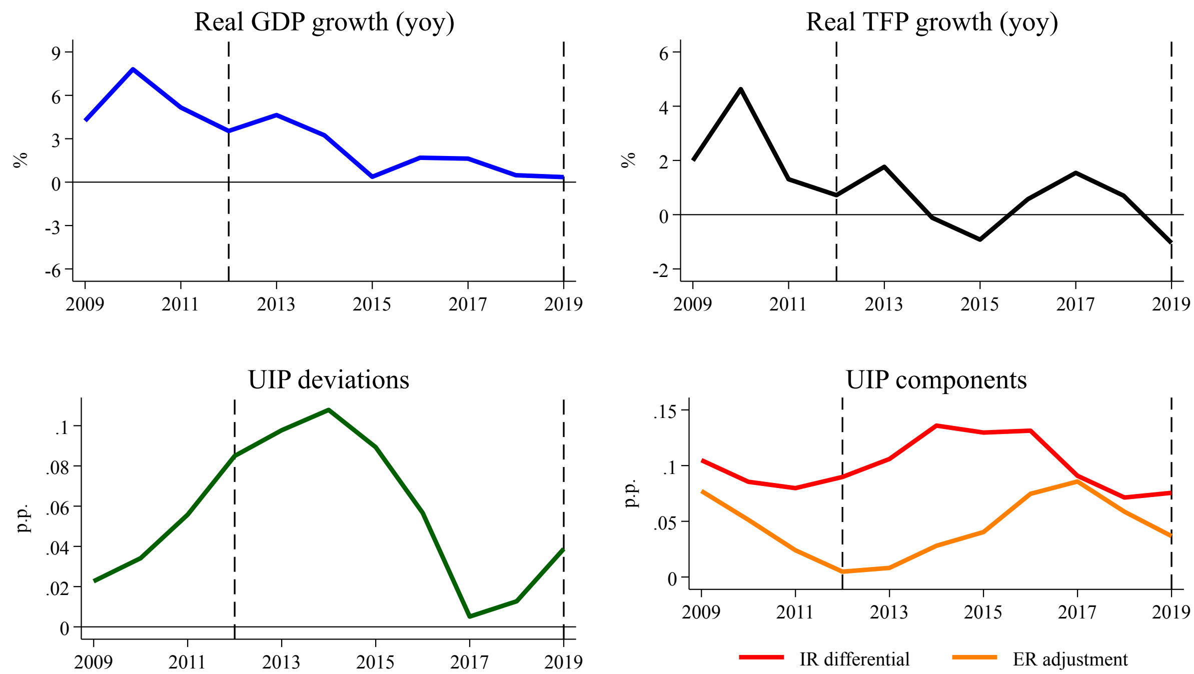
Table 1 also shows that the maturity of more than half of the firm's bank debt was less than a year (short-term (ST) + medium-term (MT)). The prevalence of short-term borrowing can be indicative of working capital needs. Similarly, Table 1 shows the proportion of US dollar

[4] We also have results using UIP deviations based on 12-month peso and dollar aggregate loan rates of Uruguayan banks.

[5] By the end of 2015, the zero lower bound period ended as the Fed started rising its rates, which is picked up by both the decline in the interest rate differential and by the increase in the expected depreciation. In addition, movements in expected depreciation during this period are highly correlated (negatively) with commodity prices.

debt for each maturity level. We show that the proportion of dollar debt is increasing with maturity.

Figure 2: Macroeconomic and Financial Background



Note: this figure plots real GDP growth (yoy), real TFP growth (yoy), 12-month UIP deviations using government bond rates and its components (interest rate differential and exchange rate adjustment). UIP deviations are calculated as in equation 20. Interest rate differential are defined in logs as $r_t^{pesos} - r_t^{USD}$ while the exchange rate adjustment is defined in logs as $s_{t+h}^e - s_t$. Dashed vertical lines indicate the period under study: 2012-2019.

Table 1: Currency and maturity of bank debt

	Bank debt (%)						
Exporter	USD	ST	ST in USD	MT	MT in USD	LT	LT in USD
No	62.6	23.5	44.8	31.6	62.2	44.9	68.1
Yes	79.0	36.5	71.3	36.9	77.4	26.6	87.0

Note: ST= less than 3 months, MT=[3 months, 1 year], LT= more than 1 year. Exporter dummy equals one if the firm had positive exports during the period 2012-2019.

With respect to the type of guarantees used by the firms, we follow the classification of Camara and Sangiacomo (2022) to distinguish between collateral-based and cash flow-based debt contracts in the guarantees listed in the Accounting Standards for Financial Intermediation Companies of the Central Bank of Uruguay (*Normas Contables para las Empresas de Intermediación Financiera*). Collateral-based lending is based on the liquidation value of assets, including real estate, machinery, equipment, land, livestock, account receivables by large firms and financial assets. Cash flow-based debt is based on current and future firm's cash flows. We find that Uruguayan firms borrowed the most against cash flow guarantees during this period, as we show in Table 2.[6]

Table 2: Composition of Uruguayan firms' debt: collateral vs cash flow-based

Category	Share of debt (%)
Collateral-based debt	28.7
Cash flow -based debt	71.3

Note: average guarantees used. Time frame: 2012-2019

5 Empirical analysis

5.1 Misallocation measures

We follow the model assumptions of CES demand and CRS technology to construct measures of MPRK and MRPL as follows:

$$MRPK_{ist} = \frac{\alpha_s}{\rho}\frac{p_{ist}y_{ist}}{k_{ist}} \text{ , where } \rho = \frac{\sigma}{\sigma - 1} \tag{21}$$

$$MRPL_{ist} = \frac{1-\alpha_s}{\rho}\frac{p_{ist}y_{ist}}{n_{ist}} \tag{22}$$

We calibrate α_s to capital cost shares at the four-digit ISIC industry level and $\sigma = 3$ following Hsieh and Klenow (2009).[7] We measure the nominal value added of the firm ($p_{ist}y_{ist}$) as operating revenue.[8] Capital stock (k_{ist}) is measured with the book value of tangible and intangible fixed assets deflated with the implicit investment price deflator of the BCU. Labor input (n_{ist}) is measured as the number of dependent and independent employees. We drop firm-year observations with missings or zeros in operating revenue, total number of employees, and fixed assets; and winsorize at the 1st and 99th percentiles. More details on how we cleaned the data can be found in Appendix A.1.

We measure misallocation as dispersion (variance) in marginal revenue products within four-digit ISIC industries. As robustness, we measure the dispersion as the difference between the 90-10th percentiles and the 75-25th percentiles of $logMRPK$. We focus on within industry dispersion because it is empirically challenging to determine whether dispersion across industries is reflecting true distortions or just differences in production technologies. We aggregate using simple averages across industries to match the representative industry of the model. The results are robust to using industry-specific weights based on value added.

[6] Camara and Sangiacomo (2022) find similar results for Argentina, neighbour country of Uruguay.

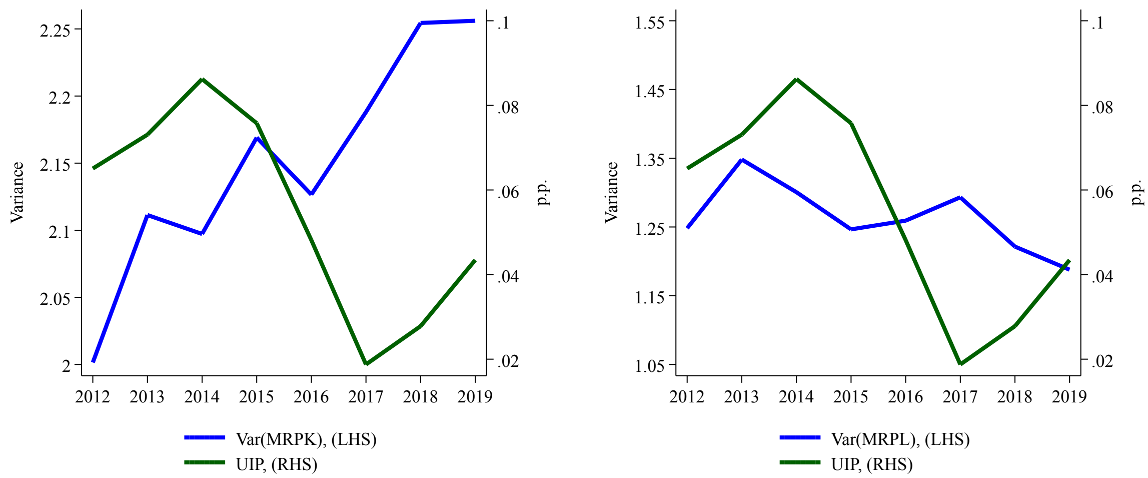
[7] Theoretically, the relevant weights are output elasticities divided by returns to scale. However, under the assumption of CRS technology, cost shares are equal to the elasticities of the output.

[8] The results hold if we substract materials.

5.2 Key empirical moments

Misallocation in the data. In Figure 3 we plot the dispersion in marginal revenue products of capital and labor together with the UIP deviations, all in logs. The first observation is that since both variances are always greater than zero, there is steady state misallocation in Uruguay. The second observation is that during this period, capital misallocation increased at the same time UIP deviations were mostly declining. Labor misallocation remained stable during this period; which is a result also found in Gopinath et al. (2017) in southern European countries during 1999-2012.[9]

Figure 3: Misallocation and UIP deviations over time



Note: this figure plots variance of log(MRPK) and log(MRPL) and UIP deviations in logs defined as in equation 20.

Misallocation and TFP. Since labor misallocation remained quite stable during this period, we focus on understanding the drivers of capital misallocation. We rely on expression 18 (which we re-paste below) to get back of the envelope calculations of the contribution of capital misallocation to aggregate TFP in this timeframe:

$$dlog(TFP) = -\frac{\alpha^2(\sigma-1)+\alpha}{2} d\mathbb{V}ar(logMRPK_i)$$

We calibrate $\sigma = 3$ as in Hsieh and Klenow (2009) and $\alpha = 0.32$ as in Mendoza (2010). During 2012-2019, aggregate TFP decreased by approximately six p.p. and capital misallocation increased by nine and a half p.p., implying a decline in aggregate TFP of two and a half p.p..

[9]The results are robust to using the difference between the 90th vs 10th percentiles, or the 75th vs 25th percentiles of $logMRPK$ to measure dispersion.

Misallocation and UIP deviations. To gauge how much of this increase in capital misallocation is driven by UIP deviations, we run Jordà (2005)-style panel local projections:

$$\mathbb{V}ar(logMRPK_{s,t+h}) = \alpha_s + \beta_h log(UIP_t) + \varepsilon_{s,t+h} \tag{23}$$

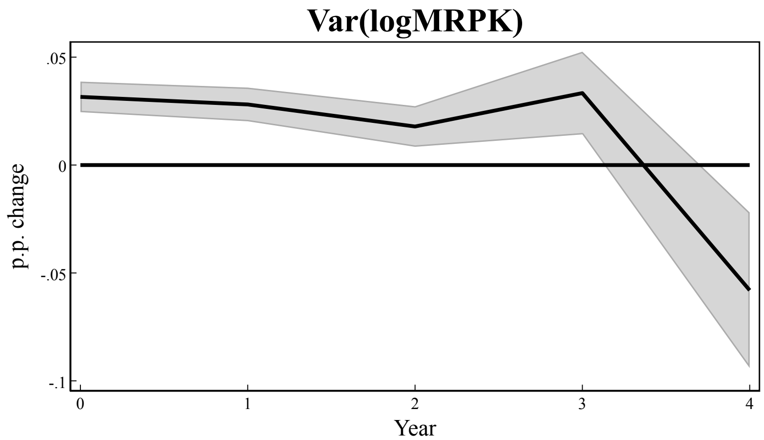
where $\mathbb{V}ar(logMRPK_{s,t+h})$ is the variance of $logMRPK$ in industry s, α_s are four-digit industry fixed effects, and $log(UIP_t)$ is the UIP deviation at time t defined in logs as the inverse of equation 19.[10] We standardize $log(UIP_t)$ over the entire sample so that its units are standard deviations in our sample. The impulse is a one standard deviation decline in UIP deviations (peso borrowing becomes relatively cheaper), matching what we observe during this period.The coefficient of interest is β_h, which captures the elasticity of the dependent variable to a decline in the relative cost of peso borrowing (i.e., a decrease in UIP deviations) at time t on outcomes over the next $t+h$ horizons, with $h = 4$. We provide in Figure 4 the impulse response function (IRF).[11]

Figure 5 shows that a one standard deviation decline in the relative cost of peso borrowing (as captured by a decrease in UIP deviations)—which we observe, for instance, between 2015 and 2016— generates an increase of approximately four p.p. contemporaneously and a cumulative increase in capital misallocation of 11 p.p. in the following three years. The results are robust to other measures of dispersion, including the difference between the 90-10 percentiles and the 75-25 percentiles of $logMRPK$. We conclude that declines in UIP deviations are associated with substantial increases in misallocation, and hence with a deterioration of aggregate TFP.

[10] We are taking the change in the UIP deviation as exogenous in this specification for two reasons. First, because it is an aggregate shock in a firm-level regression. Second, because as shown in Di Giovanni et al. (2022) and Kalemli-Özcan and Varela (2021), global risk sentiments such as VIX explain a large portion of the time variation of the UIP wedge in emerging markets.

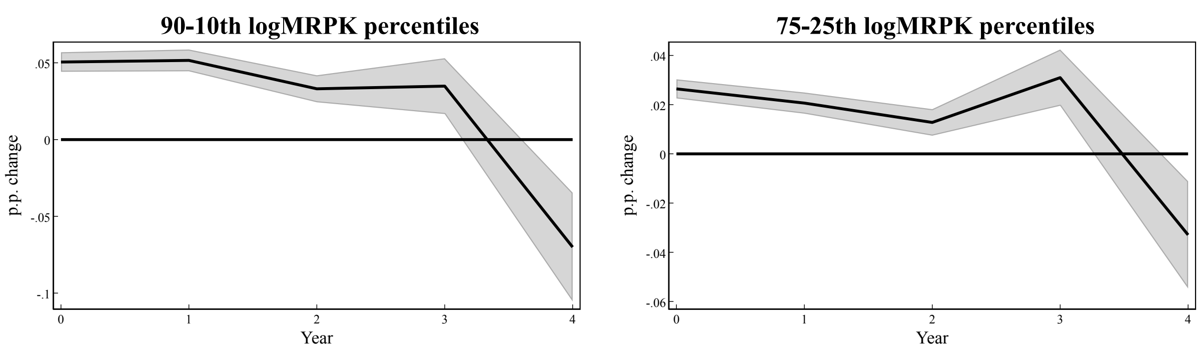
[11] The results are robust to controlling for lags of: dependent variable, UIP, and sector averages of capital and employment.

Figure 4: IRF of capital misallocation to UIP deviations



Note: this figure plots the impulse response of a one percentage point decline in the relative cost of peso borrowing (as captured by a decrease in UIP deviations), obtained from running panel local projections (specification 23). 90% confidence intervals are shown by the shaded areas. Standard errors are clustered at the firm level. Dependent variable is variance of $logMRPK$. Controls include four-digit industry dummies. The results are robust to adding one lag of: UIP deviation, dependent variable and sector size controls (capital stock and number of employees).

Figure 5: IRF of capital misallocation to UIP deviations with alternative dispersion measures



Note: this figure plots the impulse response of a one percentage point decline in the relative cost of peso borrowing (measured as a decrease in UIP deviations), obtained from running panel local projections (specification 23). The dependent variables are the differences between the 90th–10th percentiles and the 75th–25th percentiles of $\log MRPK$. 90% confidence intervals are shown by the shaded areas. Standard errors are clustered at the firm level. Controls include four-digit industry dummies. The results are robust to adding one lag of the UIP deviation, the dependent variable, and sector size controls (capital stock and number of employees).

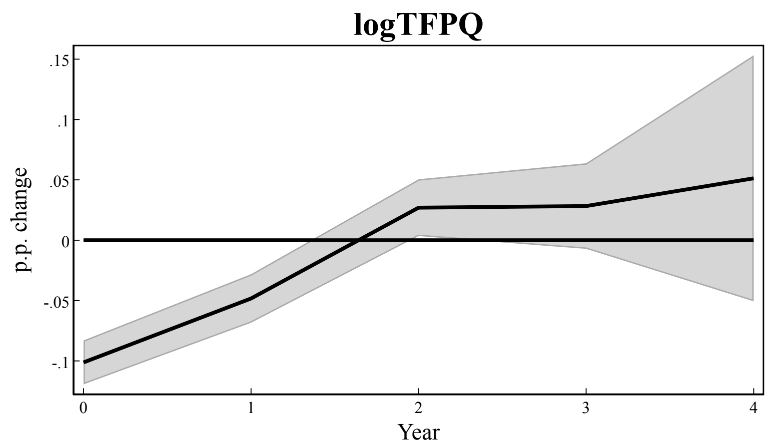
TFP and UIP deviations. As a reduced form test, we regress UIP deviations on firm level productivity, as follows:

$$logTFPQ_{is,t+h} = \alpha_s + \beta_h log(UIP_t) + \varepsilon_{s,t+h} \tag{24}$$

where $logTFPQ_{is,t+h}$ is the productivity of firm i, in industry s in period $t+h$. We construct productivity following Hsieh and Klenow (2009) $TFPQ_{ist} = \kappa_{st}\frac{(p_{ist}y_{ist})^{\frac{\sigma}{\sigma-1}}}{k_{ist}^{\alpha}n_{ist}^{1-\alpha}}$ where $\kappa_{st} = (P_{st}Y_{st})^{\frac{-1}{\sigma-1}}/P_{st}$.

We find that within narrowly defined industries, a one-standard deviation decrease in UIP deviations reduces average firm productivity by 12 p.p. in the first two years after the change (cumulatively), as shown in Figure 6.[12]

Figure 6: IRF of productivity to UIP deviations



Note: this figure plots the impulse response of a one percentage point decline in the relative cost of peso borrowing (i.e., a decrease in UIP deviations), obtained from running panel local projections (specification 23). 90% confidence intervals are shown by the shaded areas. Standard errors are clustered at the firm level. Dependent variable is firm level productivity, $logTFPQ$, defined as in Hsieh and Klenow (2009). Controls include four-digit industry dummies. The results are robust to adding one lag of: UIP deviations, dependent variable and size controls (capital stock and number of employees).

Next, we investigate the mechanisms by which UIP deviations can lead to capital misallocation. We focus on currency mismatches and dollar/peso borrowing as potential mechanisms. Movements in UIP deviations change the incentives of firms to borrow in different currencies given their characteristics, and hence impact on the degree of their currency mismatch. With this mechanism, we first center on explaining steady state misallocation, and then on explaining dynamic misallocation.

6 Inspecting the mechanisms

6.1 Variance decomposition

To disentangle the role of currency mismatches and dollar/peso borrowing as the mechanisms by which UIP deviations can impact on allocative efficiency and aggregate activity,

[12]The results are robust to controlling for lags of: dependent variable, UIP deviations, and indicators of size (capital stock and number of employees).

we decompose total dispersion of log marginal revenue products of capital $\mathbb{V}(logMRPK_i)$ derived in the model section 2, into a between and within mismatch group component:

$$\begin{aligned}\mathbb{V}(logMRPK_i) &= \mathbb{V}\Big(\mathbb{E}(logMRPK_i|mismatch)\Big) + \mathbb{E}\Big(\mathbb{V}(logMRPK_i|mismatch)\Big)\\ &= \underbrace{\sum_{j\in\{m,mm\}} w_j(\overline{logMRPK}^j - \overline{logMRPK})^2}_{\text{between } (\mathbb{V}_b)} + \underbrace{\sum_{j\in\{m,mm\}} w_j \sum_i \frac{w_j^i}{w_j}(logMRPK_i^j - \overline{logMRPK}^j)^2}_{\text{within } (\mathbb{V}_w)}\end{aligned} \tag{25}$$

where $logMRPK_i^j$ is the log marginal revenue product of capital of firm i of type j, $\overline{logMRPK}^j$ is the average mrp in a given mismatch group, $\overline{logMRPK}$ is the average $logMRPK$ in the economy, w_j is the weight of mismatch group j, w_j^i is the weight of firm i, and $\frac{w_j^i}{w_j}$ is the weight of firm i in mismatch group j. The left-hand side of expression 25 is the total variance ($\mathbb{V}$), while the right-hand side is equal to the sum of the between ($\mathbb{V}_b$) and within ($\mathbb{V}_w$) group variance.

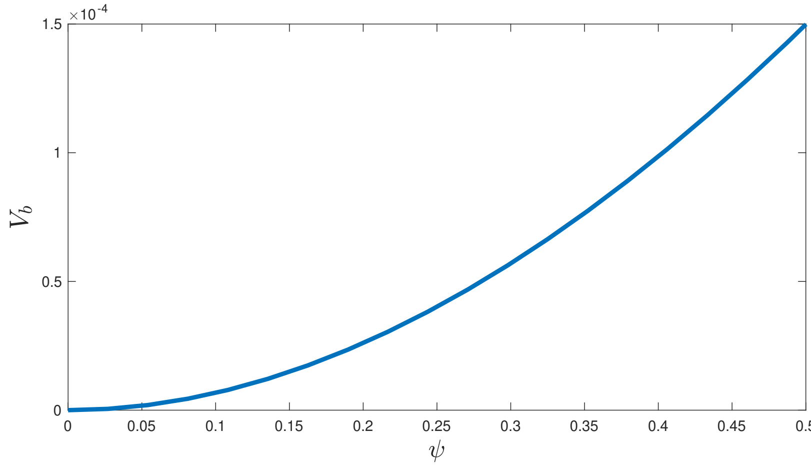
Since the only firm heterogeneity in the model is the currency mismatch, total variance equals the between variance component:

$$\mathbb{V}(logMRPK_i) = \mathbb{V}_b(logMRPK_i) \tag{26}$$

What we want to show is that if currency mismatches matter for allocative efficiency and aggregate activity, then $\mathbb{V}_b$ must be economically significant, that is, we expect to see differences in the means of $logMRPK$ of mismatched and matched firms.

Given factor prices R^k, the borrowing constraint parameter θ, the average currency mismatch in the economy γ, and the direction of deviation of the UIP, we show that there is a direct mapping between $\mathbb{V}_b$ and ψ, the working capital parameter. In particular, we find that $\mathbb{V}_b$ increases in ψ. This is because ψ directly impacts the firm-level heterogeneity of the model, namely, the currency mismatch. For a given level of UIP deviation, a higher ψ will amplify this heterogeneity, producing a higher dispersion of marginal revenue products of capital. A higher ψ implies that firms have larger working capital needs, i.e., financial frictions are tighter. We illustrate this result numerically in Figure 7 and summarize it in Proposition 2.

Figure 7: Between variance and the working capital parameter



Note: $\mathbb{V}_b$ is the between variance of $logMRPK$ and ψ is the working capital parameter. Calibration: $\theta = 0.8$, $R^k = 100$, $\gamma = 0.4$ and $UIP = 1.04$ to match the average Uruguayan data for the period under study.

Proposition 2: Given factor prices R^k, the borrowing constraint parameter θ, the average currency mismatch in the economy γ, and UIP deviation, there is a direct mapping between the between mismatch group variance $\mathbb{V}_b$ and the working capital parameter ψ:

- *if $\psi > 0$, $\mathbb{V}_b = f(\psi|R^k, \theta, \gamma, UIP)$, where $f(.)$ is an increasing function*

Putting together expressions 15, 17 and 26, we can express aggregate output in logs:

$$logY = logA - \frac{\alpha(1 + \alpha\sigma - \alpha)}{2}\mathbb{V}_b(logMRPK_i) + \alpha log(K) + (1 - \alpha)log(N) \tag{27}$$

We then derive the partial derivative of aggregate output with respect to the dollar borrowing cost R^{b*}, which we denote by $\frac{\partial logY}{\partial R^{b*}}$. The objective is to understand what happens to aggregate output if starting from a stationary equilibrium we increase R^{b*} by ϵ, $\epsilon > 0$ (i.e., we lower UIP deviations). We get that:

$$\frac{\partial logY}{\partial R^{b*}} = -\alpha(1 + \alpha\sigma - \alpha)\gamma(1 - \gamma)\frac{\psi}{1 - \psi + \psi R^{b*}}(logMRPK^{mm} - logMRPK^{m}) \tag{28}$$

The sign of expression 28 depends on the sign of $(logMRPK^{mm} - logMRPK^{m})$:

$$\begin{aligned}\frac{\partial logY}{\partial R^{b*}} &\leq 0 \text{ when } logMRPK^{mm} - logMRPK^{m} \geq 0 \Leftrightarrow R^{b*} \geq R^{b} \Leftrightarrow UIP \leq 1 \\ &\geq 0 \text{ when } logMRPK^{mm} - logMRPK^{m} \leq 0 \Leftrightarrow R^{b*} \leq R^{b} \Leftrightarrow UIP \geq 1\end{aligned} \tag{29}$$

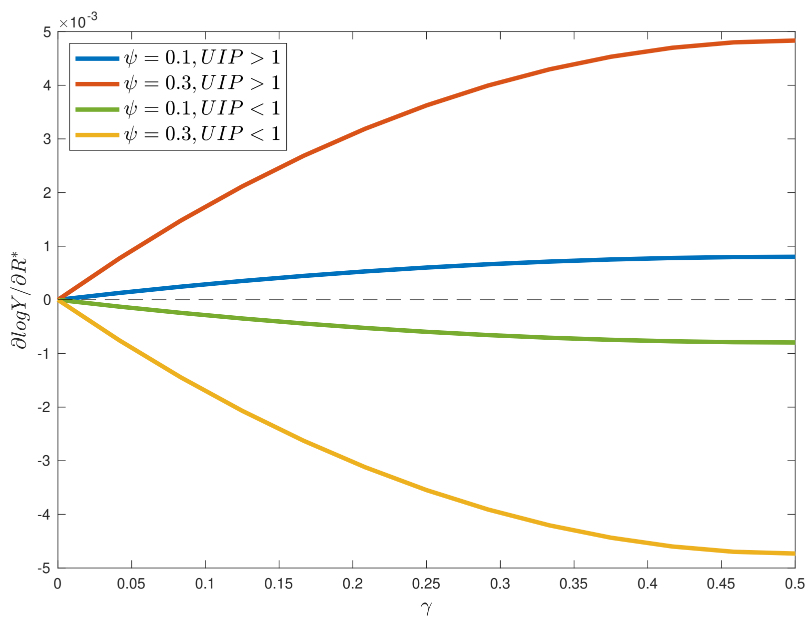
This means that if the UIP deviation that firms face in the stationary equilibrium is less than 1, moving to an equilibrium with even a lower UIP deviations will lower allocative efficiency and hence aggregate activity ($\frac{\partial logY}{\partial R^{b*}} \leq 0$), even if the change in UIP is marginal. However, if the initial UIP is greater than 1, moving to an equilibrium with a lower UIP will have a positive impact on allocative efficiency and aggregate output ($\frac{\partial logY}{\partial R^{b*}} \geq 0$).

In Figure 8, we provide a numerical illustration of $\frac{\partial logY}{\partial R^{b*}}$ against the level of currency mismatch in the economy γ. We plot it for different levels of the working capital parameter ψ. We also see that in the absence of currency mismatches ($\gamma = 0$), $\frac{\partial logY}{\partial R^{b*}} = 0$. This is because when all firms borrow in pesos, fluctuations in the borrowing cost of dollars will have no effect on the economy. In the presence of currency mismatches ($\gamma > 0$), the sign of the correlation between $\frac{\partial logY}{\partial R^{b*}}$ and γ depends on the initial direction of the UIP deviation, as we showed in 29. The strength of this relation in absolute value is increasing in the working capital parameter ψ: the larger ψ, the stronger the effect of currency mismatches on $\frac{\partial logY}{\partial R^{b*}}$. This is because a high ψ amplifies the effect of mismatch on aggregate activity by increasing the financial constraints firms face, while a low ψ dampens it, as we show in Proposition 2. We summarize the key takeaways in Proposition 3.

Proposition 3: if starting from a stationary equilibrium we increase R^{b*} by ϵ, $\epsilon > 0$ (i.e., we lower UIP), and compute $\frac{\partial logY}{\partial R^{b*}}$ we get that:

1. *if $\gamma = 0 \Rightarrow \frac{\partial logY}{\partial R^{b*}} = 0$*
2. *if $\gamma > 0$ and $UIP > 1 \Rightarrow Corr(\frac{\partial logY}{\partial R^{b*}}, \gamma) > 0$*
3. *if $\gamma > 0$ and $UIP < 1 \Rightarrow Corr(\frac{\partial logY}{\partial R^{b*}}, \gamma) < 0$*
4. *$|\frac{\partial(\partial logY/\partial R^{b*})}{\partial \gamma}| = f(\psi)$, where $f(.)$ is an increasing function*

Figure 8: Currency mismatches and aggregate output



Note: γ is the fraction of mismatched firms in the economy and $\frac{\partial logY}{\partial R^*}$ is partial derivative of aggregate output with respect to the dollar borrowing cost (i.e., we lower UIP deviations). Calibration: $\sigma = 3$ as in Hsieh and Klenow (2009), $\alpha = 0.32$ as in Mendoza (2010), $\theta = 0.8$, $R^k = 100$, $UIP > 1 = 1.04$, $UIP < 1 = 0.96$.

Finally, we derive Proposition 4 by combining Propositions 2 and 3. We show that given model assumptions, $\mathbb{V}_b$ is a sufficient statistic that summarizes the extent to which currency mismatches matter for steady state allocative efficiency and aggregate activity, which we can measure in the data.

Proposition 4: Proposition 2 shows that the working capital parameter ψ can be mapped to the between mismatch group variance $\mathbb{V}_b$ for a given UIP deviation, and Proposition 3 shows that the strength of the impact of currency mismatches on $\frac{\partial logY}{\partial R^{b*}}$ is an increasing function of ψ for a given UIP deviation. This makes V_b a sufficient statistic that summarizes the extent to which currency mismatches matter for steady state allocative efficiency and aggregate activity. This is true under the model assumptions, that is, CES demand, CRS production function, partial equilibrium, and currency mismatches are the only source of firm heterogeneity.

6.2 Empirical measurements

Currency mismatch measure. We construct a baseline measure of currency mismatch at the firm level and several alternative measures that we discuss in Appendix A.2. The baseline measure relies on the difference between assets and liabilities in dollars. In Uruguay, the use of FX hedging is very limited, but we have data for this in the asset and liability decomposition by currency, depending on the position they are taking.

We construct the currency mismatch of a firm i at time t and normalize it by total assets, as follows:

$$\frac{\text{mismatch}_{it}}{\text{total assets}_{it}} = \frac{\text{assets}_{it}^{USD} - \text{liabilities}_{it}^{USD}}{\text{total assets}_{it}} \tag{30}$$

Using 30 we build a firm level time-invariant dummy using the following rule: if the firm had an average mismatch to total assets below the median of the firms' means, we classify it as mismatched, otherwise we classify it as matched.

We find that approximately 37% of the Uruguayan firms have some degree of mismatch.[13] We provide in Appendix A.3 a decomposition of currency mismatch and dollar borrowing by industry. We find that firms in Services and Food and Accommodation are mismatched the most (above 50%), while those in Manufacturing and Retail are mismatched the least (below 33%). The alternative mismatch measures use different criteria to define mismatch, and one of them is a categorical variable (no mismatch, mismatch, high mismatch) instead of a dummy.

Variance decomposition in the data. We calculate the between (V_b) and within (V_w) mismatch group variance decomposition in the data following 25, to investigate how much of

[13]The only publicly available benchmark of currency mismatch in Uruguay is the implicit exchange rate risk of banks, developed by the BCU. The indicator is constructed as the ratio of credit to the non-tradable sector in foreign currency over total credit. Non-tradable sectors are defined as those that export less than 20% of their gross production value (indirect exports are also considered for some agricultural sectors). The implicit exchange rate risk of banks ranged between 25% and 33% during this period, and 28% on average, which is not far from our estimates. Unfortunately, this measure is constructed at the sector level and therefore assumes homogeneity within sectors and therefore across firms.

economy-wide steady state dispersion is accounted for by steady state currency mismatch. We summarize the results in Table 3.

Table 3: Variance decomposition by mismatch group

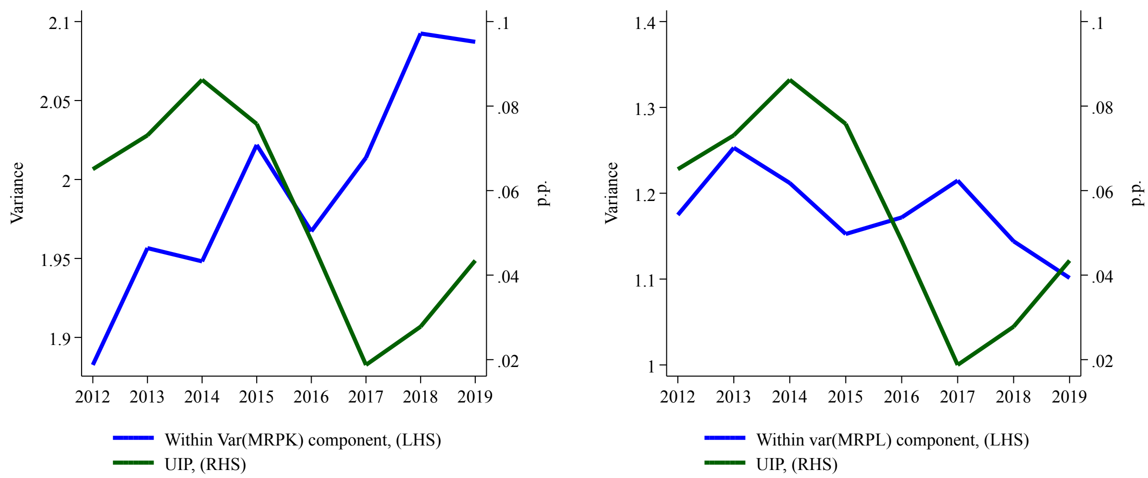
	Total	Between/Total	Within/Total
log(MRPK)	2.151	0.063	0.937
log(MRPL)	1.263	0.058	0.942

Note: to construct this table we calculate the average misallocation measures by mismatch group using our static mismatch dummy, and we do so for each four-digit industry. Then we aggregate using simple averages.

Interestingly, we find that the between group variance cannot explain on average more than 6% of total steady state variance, of both capital and labor. We run several robustness tests that include: i) using the alternative mismatch measures (different definitions of mismatch and a categorical variable instead of a dummy), ii) dropping exporters, i.e., comparing firms that sell in pesos but have debt in peso vs dollars, and iii) changing the industry level aggregation (no industry weights, with industry weights); and find that in none of these cases V_b can explain more than 8-10% of steady state misallocation. The implication is that static currency mismatches do not seem to be a source of steady state misallocation. Through the lens of our model, a low between variance component implies that the degree of financial frictions is low.

However, mismatch is not really a static concept; it can change over time with UIP deviations. For this reason, we focus on what is moving with the UIP deviations during this period to see if we can explain the observed dynamic misallocation. We find that it is the within variance component that explains dynamic misallocation, as we show in Figure 9. The within variance component tracks very closely the total variance of capital and labor plotted in Figure 3, i.e., it is increasing for capital and more stable for labor.

Figure 9: Within variance component and UIP deviations over time



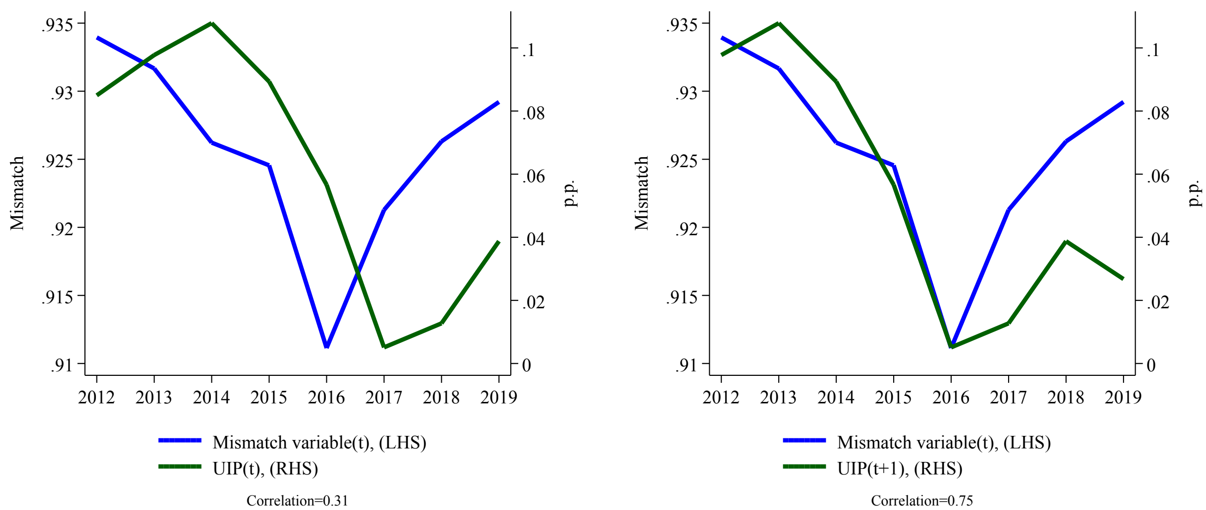
Note: this figure plots the within variance component of log(MRPK) and log(MRPL) and UIP deviations in logs defined as in equation 20.

With further empirical analysis, we try to understand what is driving the dynamic correlation of the within variance component with UIP deviations.

6.3 Dynamic misallocation

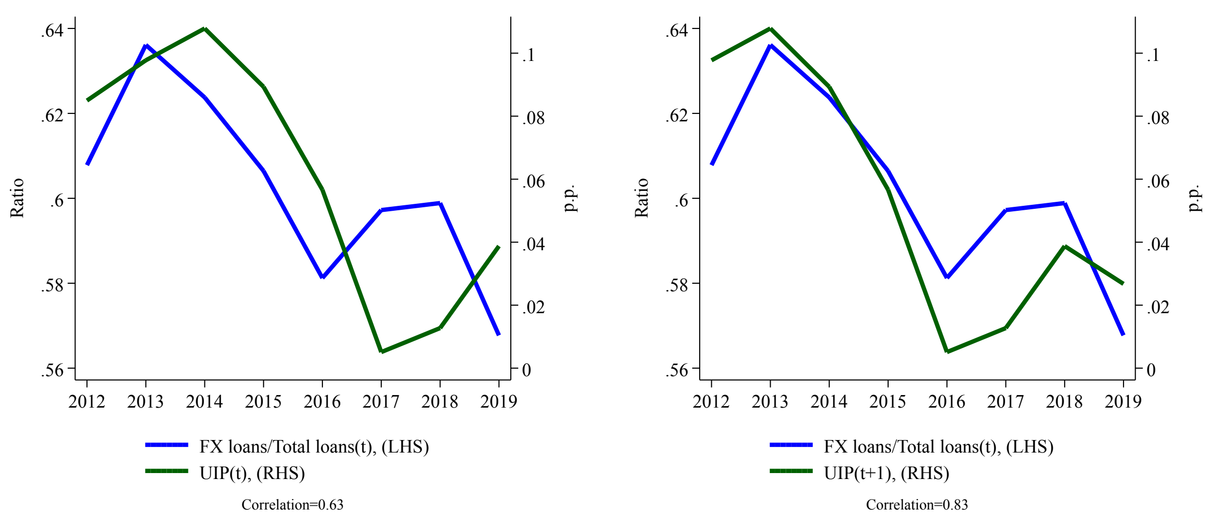
UIP deviations (relative borrowing costs), dollar borrowing and currency mismatch. In Figure 10 we show that the correlation between time-varying currency mismatch and UIP deviations is strong and positive. In this case, we use the three-category time-varying measure of mismatch (0 if no mismatch, 1 if some mismatch, 2 if high mismatch) described in Appendix A.2. We find that the contemporaneous correlation is 0.31 and the correlation with one lead of the UIP deviations jumps to 0.75. In Figure 11 we show that large positive UIP deviations increase the incentives for dollar borrowing: the contemporaneous correlation between dollar borrowing and UIP deviations is 0.63 while the correlation with one lead of the UIP deviations is 0.83. Large positive UIP deviations imply very cheap dollar rates in relative terms, making it attractive to borrow in dollars despite the currency risk it generates. Low UIP deviations dampen this incentive—firms will not be willing to hold currency risk if they can borrow in pesos for a similar rate. This observation is consistent with the recent findings of Salomao and Varela (2022), Di Giovanni et al. (2022), and Gutierrez et al. (2023), which have also documented a positive correlation between UIP deviations and dollar borrowing.

Figure 10: Currency mismatch and UIP deviations



Note: this figure plots UIP deviations in logs at time t (left plot) and at time $t + 1$ (right plot) and the categorical mismatch variable described in Appendix A.2 at time t. We use this variable instead of the mismatch dummy to capture more firm and time variation. The variable takes three values: 0 if no mismatch, 1 if some mismatch, 2 if high mismatch. UIP is defined as in equation 20.

Figure 11: FX loans and UIP deviations



Note: this figure plots UIP deviations in logs at time t (left plot) and at time $t + 1$ (right plot) and average ratio of FX loans to total loans at time t. UIP is defined as in equation 20.

Characterization of switchers vs peso borrowers. We next run regressions à la Salomao and Varela (2022) to study the characteristics of firms that sort into mismatch, both at the extensive and intensive margins. To study the extensive margin, we rely on the mismatch dummy, and to study the intensive margin, we use the ratio of FX borrowing to total borrowing from banks. In particular, we investigate whether foreign currency borrowing correlates with firm productivity, both unconditionally and conditional on size. We use the term "switchers" to denote firms that are able to switch the currency in which they borrow depending on the relative cost (UIP deviations). We follow closely Salomao and Varela (2022) specification, that were the first ones to study the link between productivity and dollar borrowing, as follows:

$$\text{mismatch}_{ist} = \alpha_{st} + \beta log(TFPQ_{ist-1}) + \Gamma X_{ist-1} + \varepsilon_{ist} \tag{31}$$

$$\text{shareFXdebt}_{ist} = \alpha_{st} + \beta log(TFPQ_{ist-1}) + \Gamma X_{ist-1} + \varepsilon_{ist} \tag{32}$$

where mismatch_{ist} is the mismatch dummy in its time varying version and $\text{shareFXdebt}_{ist-1}$ is the lagged ratio of FX debt to total bank debt of firm i in industry s. $TFPQ_{ist}$ is total factor productivity defined as in Hsieh and Klenow (2009):

$$TFPQ_{ist} = \kappa_{st} \frac{(p_{ist} y_{ist})^{\frac{\sigma}{\sigma-1}}}{k_{ist}^{\alpha} n_{ist}^{1-\alpha}} \tag{33}$$

where $\kappa_{st} = (P_{st} Y_{st})^{\frac{-1}{\sigma-1}} / P_{st}$.

X_{ist-1} are lagged firm size indicators (capital stock and number of employees). The coefficient of interest in each specification is β that captures the correlation between firm productivity and currency mismatch.

We find that within narrowly defined industries, productive firms are more likely to be mismatched and borrow in dollars more intensively, unconditionally, and conditionally on size; consistent with Salomao and Varela (2022). In other words, dollar borrowing is selective. We summarize the results in Table 4.

Table 4: Productivity, size and mismatch correlates

	(1)	(2)	(3)	(4)
	Mismatch		Share FX debt	
$\log(\text{TFPQ})_{t-1}$	0.030***	0.021***	0.028***	0.016***
	(0.006)	(0.006)	(0.006)	(0.006)
$\log(\text{size})_{t-1}$		0.030***		0.036***
		(0.005)		(0.006)
Ind x Year FE	✓	✓	✓	✓
N	12267	12267	6608	6608
adj. R^2	0.079	0.086	0.162	0.178

Note: standard errors in parenthesis and two-way clustered by four-digit industries and years. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Dependent variables are the time varying mismatch dummy and the share of FX debt which is the ratio of FX debt to total bank debt. The main explanatory variable is total factor productivity defined as in Hsieh and Klenow (2009) (equation 33). Additional controls include four-digit industry-year dummies and lagged size controls. We drop exporters as in Salomao and Varela (2022), but results are robust to adding them, and also robust to running the regressions using time averages and controlling for lagged leverage.

Next, we run a similar specification, where the dependent variable is a dummy that we refer to as *peso borrowers*. These are firms that borrow in pesos only when the UIP deviations are low enough (starting in 2016) and they do not have dollar debt. Roughly 10% of firms enter in this category and they are all part of the matched group defined in section 5.[14] The specification is as follows:

$$\text{peso borrower}_{ist} = \alpha_{st} + \beta log(TFPQ_{ist-1}) + \Gamma X_{ist-1} + \varepsilon_{ist} \tag{34}$$

We find that within narrowly defined industries, productivity and size are negatively correlated with the sorting into *peso borrowing*, as shown in Table 5. In other words, peso borrowers are more likely to be small and unproductive firms ("bad types"). In the next subsection, we come back to the role that this particular group of firms plays.

Table 5: Productivity, size and peso borrowing correlates

	(1)	(2)
	Peso Borrower	
$\log(\text{TFPQ})_{t-1}$	-0.0044**	-0.0037*
	(0.0021)	(0.0020)
$\log(\text{size})_{t-1}$		-0.0001**
		(0.0000)
Ind x Year FE	✓	✓
N	20950	20950
adj. R^2	0.030	0.032

Note: standard errors in parenthesis and two-way clustered by four-digit industries and years. * p $<$ 0.10, ** p $<$ 0.05, *** p $<$ 0.01. Dependent variable is the peso borrower dummy (firms that borrow in pesos only when UIP deviations are low enough and have no dollar debt). The main explanatory variable is total factor productivity defined as in Hsieh and Klenow (2009) (equation 33). Additional controls include four-digit industry-year dummies and lagged size controls.

How do firms adjust to changes in UIP deviations? We run Jordà (2005)-style panel local projections to understand how firms adjust their borrowing and inputs to changes in UIP deviations. We rely on the following specification, and run it by mismatch group:

$$log(Y_{is,t+h}) = \alpha_s + \beta_h log(UIP_t) + \mu log(UIP_{t-1}) + \gamma log(X_{is,t-1}) + \varepsilon_{is,t+h} \tag{35}$$

where $log(Y_{ist+h})$ is a firm-level outcome of firm i, industry s, for horizon $t+h$, α_s are four-digit industry fixed effects to compare firms within the same industry, $log(UIP_t)$ is the UIP deviation at time t defined in logs as the inverse of equation 20, $log(X_{ist-1})$ is a vector of firm lagged controls which includes a lag of the dependent variable and of firm size indicators (capital stock and number of employees). The coefficient of interest is β_h that captures the elasticity of the dependent variable to a one standard deviation decrease in the UIP deviation

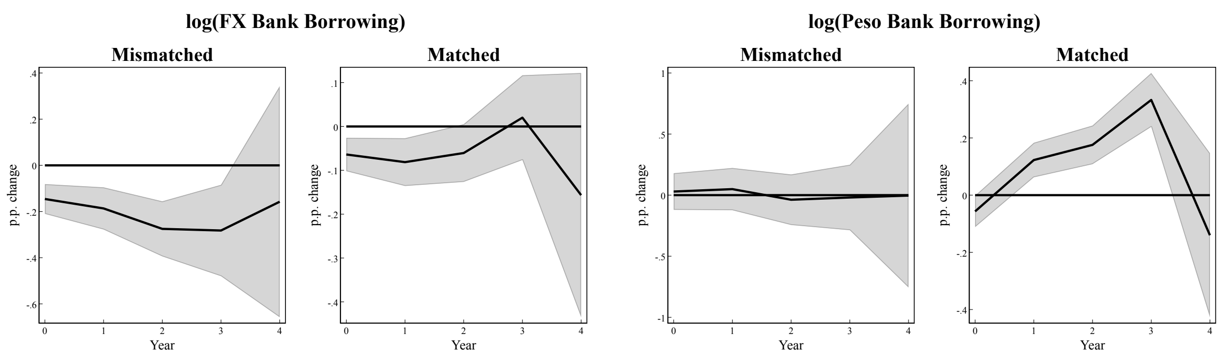
[14]We use alternative definitions for the *peso borrowers* where we move the year in which we allow them to start borrowing in pesos, and results are robust. We chose 2016 as the baseline year since UIP are arguably lower given the first years of this period.

(peso borrowing becomes relatively cheaper) at time t in the next $t+h$ horizons, with $h = 4$. We provide in Figures 12 and 13 the impulse response functions (IRFs).

We find that a one standard deviation decrease in UIP deviations makes firms decrease their FX borrowing since it became relatively more expensive. Mismatched firms cut FX debt by 27 p.p. in the second year after the change in the UIP deviation and it remains low during the following years, while matched firms cut their dollar borrowing by six p.p. over the second year after the change in UIP. When UIP deviations are low, firms are not willing to borrow in dollars and hold currency risk if they have access to peso borrowing for a similar rate. We find that on average, matched firms increase peso borrowing by roughly 33 p.p. in the third year after the decline in UIP deviations, while we do not see significant results for mismatched firms.

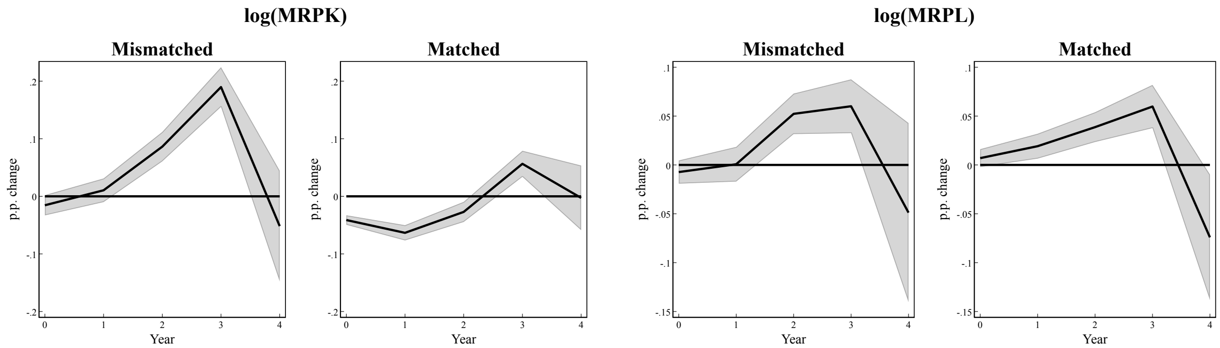
As a result of the currency switching of firms' borrowing, we find that a one standard deviation decrease in UIP deviations worsens capital and labor distortions of mismatched firms, i.e., both $log(MRPK)$ and $log(MRPL)$ go up. However, the decline in UIP deviations alleviates capital distortions of matched firms for up to two years after the shock for six p.p. on average, but worsens their labor distortions.

Figure 12: IRFs of access to financing



Note: this figure plots impulse responses of a one standard deviation decrease in UIP deviations obtained from running panel local projections (specification 35). 90% confidence intervals are shown by the shaded areas. Standard errors are clustered at the firm level. Dependent variables include: FX and peso borrowing from banks; all in logs and in domestic currency. Controls include four-digit industry dummies, and one lag of: UIP deviation, dependent variable and firm size controls (capital stock and number of employees).

Figure 13: IRFs of misallocation measures



Note: this figure plots impulse responses of a one standard deviation decrease in UIP deviations obtained from running panel local projections (specification 35). 90% confidence intervals are shown by the shaded areas. Standard errors are clustered at the firm level. Dependent variables include: $log(MRPK)$ and $log(MRPL)$ for matched and mismatched groups. Controls include four-digit industry dummies, and one lag of: UIP deviation, dependent variable and firm size controls (capital stock and number of employees).

Overall, we find that deviations of the UIP, which is a financial variable and as such constitutes a temporary change, not only are it able to generate economically and statistically significant effects, but also generate some persistence in the transitionary dynamics. We find that all firm outcomes start to revert after year three of the change in the UIP deviation.

Who drives the results? To study the role of peso borrowers and switchers, we augment specification 35 as follows:

$$log(Y_{is,t+h}) = \alpha_s + \alpha_i^{peso} + \beta_{1h} log(UIP_t) + \beta_{2h} log(UIP_t)\alpha_i^{peso} + lags + \varepsilon_{is,t+h} \tag{36}$$

where α_i^{peso} is a dummy that equals one if the firm only borrows in pesos when UIP deviations are low. As we have shown before, $\alpha_i^{peso} = 1$ are the "bad types", that is, small unproductive firms. The term $lags$ includes: a lag in the deviations of the UIP, and the vector $log(X_{is,t-1})$ from equation 35 of lagged variables at the firm level.

In this case, the coefficients of interest are given by equations 37 and 38 that capture the effect of a one standard deviation decline in UIP deviations on the variable of interest $log(Y_{is,t+h})$, depending on the value of α_i^{peso}:

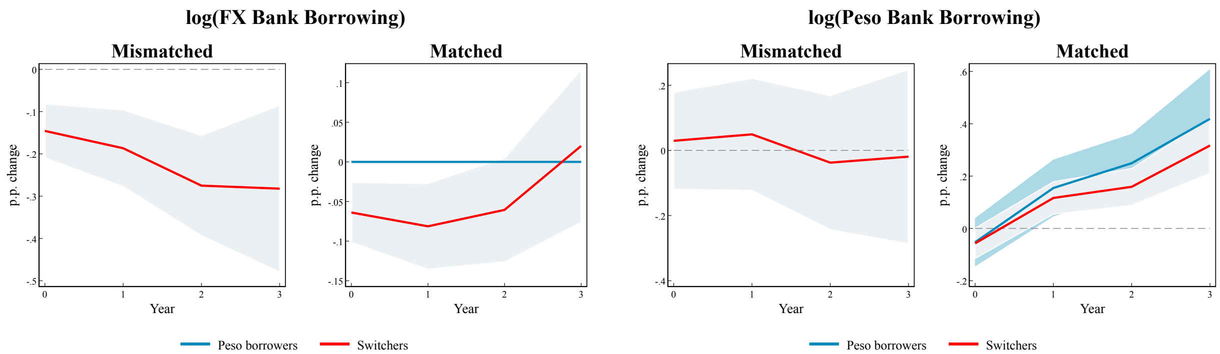
$$\left.\frac{\partial log(Y_{is,t+h})}{\partial log(UIP_t)}\right|_{\alpha_i^{peso}=1} = \beta_{1h} + \beta_{2h} \tag{37}$$

$$\left.\frac{\partial log(Y_{is,t+h})}{\partial log(UIP_t)}\right|_{\alpha_i^{peso}=0} = \beta_{1h} \tag{38}$$

In Figures 14 and 15 we plot the coefficients over time. We refer to $\alpha_i^{peso} = 0$ as *switchers* since these firms switch the currency in which they borrow depending on the UIP deviation, while $\alpha_i^{peso} = 1$ are the *peso borrowers*. For better visualization, we only plot the IRFs until $h = 3$ in this case.

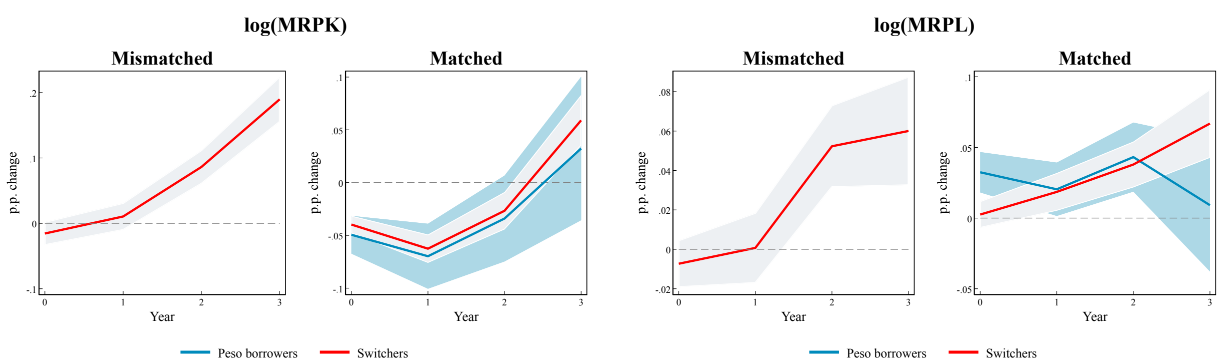
We find that lower UIP deviations make peso borrowing more accessible, enabling, in particular, the "bad types" to access financing and drive the increase in peso borrowing we observe in the matched group (Figure 14). The fact that small unproductive firms can access peso financing when UIP is low is what we argue generates dynamic misallocation. We also show how marginal revenue products respond as a result and find that capital distortions are alleviated mainly for peso borrowers when the UIP decreases (Figure 15).

Figure 14: IRFs of access to financing—switchers vs peso borrowers



Note: this figure plots impulse responses of a one standard deviation decrease in UIP deviations obtained from running panel local projections (specification 36). 90% confidence intervals are shown by the shaded areas. Standard errors are clustered at the firm level. Dependent variables are firm FX and peso borrowing from banks; all in logs and in domestic currency. Controls include four-digit industry dummies, and one lag of: UIP deviation, dependent variable and firm size controls (capital stock and number of employees).

Figure 15: IRFs of misallocation measures—switchers vs peso borrowers



Note: this figure plots impulse responses of a one standard deviation decrease in UIP deviations obtained from running panel local projections (specification 36). 90% confidence intervals are shown by the shaded areas. Standard errors are clustered at the firm level. Dependent variables are firm-level $log(MRPK)$ and $log(MRPL)$. Controls include four-digit industry dummies, and one lag of: UIP deviation, dependent variable and firm size controls (capital stock and number of employees).

7 Conclusion

In this paper, we study the relationship between resource misallocation and UIP deviations and focus on currency mismatches and dollar/peso borrowing as the underlying mechanism that links them. We make two main contributions of potential interest to policy makers.

First, in a static theoretical model, we show that when firms borrow in different currencies, UIP deviations lead to heterogeneous borrowing costs that can generate capital misallocation if firms have the same productivity. Using annual firm-level data from Uruguay for the period 2012-2019, we find that decreases in UIP deviations are associated with substantial increases in capital misallocation, which explains most of the observed increase in misallocation during this period and of the slowdown in aggregate TFP.

Second, we focus on currency mismatches and dollar/peso borrowing as potential mechanisms by which UIP deviations can lead to steady state and dynamic capital misallocation. In the model, we decompose the variance of $log(MRPK)$, our measure of misallocation, by mismatch to obtain a between and within- mismatch variance component. We show that the between mismatch group variance component is a sufficient statistic that summarizes the extent to which currency mismatches matter for static allocative efficiency and hence aggregate activity. We find empirically that the between variance component, cannot explain on average more than 6% of total steady state misallocation, even when roughly 40% of firms are mismatched in Uruguay; suggesting that currency mismatches do not seem to be a source of steady state capital misallocation. However, dynamic capital misallocation can be explained by the within variance component. Further empirical analysis suggests that dynamic misallocation is related to firms switching the currency in which they borrow depending on the UIP deviation. We find that when UIP deviations decrease, peso borrowing becomes relatively more accessible, enabling small unproductive firms to access peso borrowing. These firms cannot borrow in dollars in the first place, because dollar borrowing is more selective, but can borrow in pesos when it is cheap enough. We find that lower UIP deviations allow bad types to access financing, directly impacting dynamic misallocation.

In future work, we plan to develop a dynamic and richer model that rationalizes our findings, allows us to establish causal relations between misallocation, UIP deviations, and dollar/peso borrowing, and study optimal policy. Some of the ingredients that we want the model to include are: i) heterogeneous firms (mismatch, productivity, financial constraints), ii) currency and time-varying constraints (currency constraints because only productive and large firms can borrow in dollars, and time-varying constraints to capture changes in the cost of borrowing), iii) default risk as in Ottonello and Winberry (2020) because of the presence of currency mismatches.

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A Appendix

A.1 Data Appendix

Our data set combines firm-level information on annual financial statements from the Annual Economic Activity Survey (*Encuesta Anual de Actividad Económica*) and the monthly credit registry of the Central Bank of Uruguay (BCU).

The Annual Economic Activity Survey is a representative survey of the universe of Uruguayan firms that have 10 or more employees. According to the national classification, the set of firms with more than 10 employees includes a portion of small firms (those with 5-19 employees) and the universe of medium (those with 20-99 employees) and large firms (more than 100 employees). All big firms are surveyed every year, while for small and medium firms, it is a rotating panel. Small and medium firms are randomly sampled and remain in the sample for at least three years, when replaced firms with similar characteristics (size and sector) take their spot. Construction, agriculture, and the public sector, which together represent less than 20% of GDP, are excluded from the survey.

The credit registry is a monthly record of all loans granted in the financial sector to firms. It reports the outstanding stocks at the end of the month and includes, among others, the borrower's id, industry, loan amount, currency, maturity, loan type, guarantee type and amount, and the borrower's credit rating.

We merge these two datasets using firm-year identifiers, and for that, we use end-of-year stocks outstanding of the credit registry. We work with a firm-year unbalanced panel for the years 2012 through 2019.

We also use aggregate data. To construct UIP we use 1 year ahead exchange rate expectations data from Consensus Economics, 1 year Uruguayan government bond rates from BEVSA (stock exchange), 1 year treasury bill rates from Bloomberg, and spot exchange rate from the IMF-IFS. We also get investment and industry specific deflators, GDP and loan rates from the BCU, and aggregate TFP data from the Penn World Table version 10.01 (Feenstra et al. (2015)).

A.1.1 Data cleaning

We implement the following steps:

1. We drop firm-year observations that have missing information on operating revenues, fixed assets, intangible capital, and employment.

2. We drop firm-year observations if any of the following variables are negative: assets, employment, operating revenues, intangible capital, fixed assets, and liabilities.

3. We drop firm-year observations if any of the following variables are zero: operating revenues, employment, intangible capital, fixed assets, liabilities.

4. We drop firm-year observations with missing information regarding their industry of activity or firm id.

5. We deflate fixed assets, intangible capital, and inventories with the investment deflator of the country while for assets, operating revenue, and all liability variables, we use the price deflator at the 2-digit industry level.

6. We cleaned the data of the credit register at the loan level and collapsed all the data at the firm-bank-currency-time period level. All debt amounts are expressed in units of current local currency (the exchange rate used by the credit register for foreign currency balances is the end-of-month rate). We reshaped the data set so that all different types of loan products and collaterals from the firm-bank pair were grouped as columns. We dropped firm-bank observations with zero debt.

7. We winsorize all variables in our dataset at the 1 and 99th percentiles so that our results are not driven by outliers. We also winsorize at the 1 and 99th percentiles all of our estimated $MRPK$, $MRPL$ and $TFPQ$.

A.1.2 Descriptive statistics

We present below in Table A1 summary statistics of the key variables used in this project.

Table A1: Summary statistics

	mean	sd	min	max	count
Value Added	17.94	1.58	13.81	23.01	30282
Fixed assets	15.82	2.28	9.61	21.47	30282
Employment	77.76	156.18	1.00	1097.00	30282
Total Assets	17.39	1.81	8.64	25.87	30282
Total Liabilities	16.24	2.08	-0.32	25.43	30282
Bank debt	15.05	2.62	6.91	22.48	16330
FX bank debt share	0.60	0.46	0.00	1.00	16330
Mismatch dummy	0.41	0.49	0.00	1.00	30282
Exporters	0.37	0.48	0.00	1.00	30282

Note: all variables are in logs and in real terms, except: employment that is in number of people and the last three variables that are either a share or a dummy. Time frame: 2012-2019.

A.2 Alternative mismatch measures

Alternative 1 relates the currency of bank debt and trade credit with the export status of the firm. We use both bank and trade credit, since they constitute the most important sources of financing for firms. The way we construct the alternative dummy follows the criteria summarized in Table A2, where 0 denotes matched firms and 1 mismatched firms.

Table A2: Construction of alternative mismatch measure (2 categories)

	USD debt only	Peso debt only	No debt	Both USD & peso debt
Exporter	0	1	0	0
Non-exporter	1	0	0	0

Note: this table shows the criteria used to construct the alternative mismatch measures. Key: 0=matched, 1=mismatched.

This methodology yields time-varying dummies for firms. To construct a time-invariant dummy, we take the mean of each firm over time. If the mean is above the median of the means, we classify it as mismatched. Otherwise, we classify it as matched.

Alternative 2 is very similar to alternative 1 but generates a categorical variable (no mismatch, mismatch, high mismatch) instead of a dummy (no mismatch, mismatch). It relies on the export status of firms and the currency of bank debt. In Table A3 we summarize the criteria we follow to construct it; where 0 denotes matched, 1 mismatched firms, and 2 high mismatch firms.

Table A3: Construction of alternative mismatch measure (3 categories)

	USD debt only	Peso debt only	No debt	Both USD & peso debt
Exporter	0	2	0	1
Non-exporter	2	0	0	1

Note: this table shows the criteria used to construct alternative 3, which is categorical. Key: 0=matched, 1=mismatched, 2=high mismatch.

To convert it to a time-invariant dummy, we do the following: If the mean is 0, or in other words, if the firm was matched on average, we classify it as matched. If the mean is between 1 and 1.5 we classify it as mismatched, and when the mean is above 1.5 we classify it as a high mismatch firm.

We summarize the results of our currency mismatch alternatives and the baseline in Table A4.

Table A4: Summary of mismatch measures

Mismatch measure	Summary	%
Baseline	Assets and liabilities by currency over of assets	37.9
Alternative 1	Bank debt and trade credit by currency and export status (2 cats)	41.6
Alternative 2	Bank debt by currency and export status (3 cats)	56.3

Note: this table summarizes the baseline and alternative mismatch measures used in this paper.

A.3 Mismatch and FX borrowing by Industry

Table A5: Share of FX borrowing by Industry

	Mean	Standard deviation
Manufacturing	0.68	0.43
Services	0.43	0.47
Retail	0.63	0.45
Mining	0.73	0.41
Food and Accommodation	0.58	0.47
Transport and Communications	0.66	0.44

Note: this table provides summary statistics of the degree of FX borrowing by industry, defined as FX debt to total debt.

Table A6: Currency mismatch by Industry

	Mean	Standard deviation
Manufacturing	0.27	0.45
Services	0.51	0.50
Retail	0.33	0.47
Mining	0.35	0.48
Food and Accommodation	0.52	0.50
Transport and Communications	0.38	0.49

Note: this table provides summary statistics of the proportion of firms with currency mismatch by industry. Currency mismatch is defined as in section 5.