Flip or Flop?
Tobin Taxes in the Real Estate Market [*]

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Abstract

We introduce a heterogeneous investor model with rental rate and pricing risk to study how policymakers should set tax rates to deter speculative housing transactions. We calibrate the model using the universe of personal income tax returns and responses to a sales tax on investment properties in Taiwan. Applying sufficient statistics or setting moderate price-rent ratio targets results in an optimal tax on property flips of 4% — close to flat transfer tax rates imposed in global real estate markets. Levying higher sales taxes on second homes increases price levels but also improves welfare for renters on the margin of homeownership.

Keywords: Tobin tax, price-rent ratio targeting, housing policy, noise trading, holding period returns, bunching, optimal corrective taxation

JEL classifications: E61, G11, G12, H21, R31, R38

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1 Introduction

Recent booms in real estate investment have fueled concerns about housing affordability and macroeconomic stability, leading policymakers in large, supply-constrained cities to call for taxes targeting speculators. However, direct evidence on the ability of anti-speculation transfer taxes to correct pricing inefficiencies in the housing market is scarce. Transfer taxes render real estate less attractive as an investment good, thus lowering demand and putting downward pressure on prices. But such taxes may also crowd out noisy trades by overoptimistic investors and reduce housing inventory, leading to overall ambiguous effects on prices, volatility, and the redistribution of wealth between renters and homeowners.

We quantify these competing demand and supply effects by introducing a heterogeneous investor model to characterize optimal corrective housing flip taxes. We extend insights from equilibrium models of financial markets by incorporating the microstructure of housing markets, including investors' tenure choices – that is, the decision of whether to rent or own – segmentation, search and liquidity costs, and heterogeneity in investment horizon, as captured by investors with different discount rates. We consider two sets of policy instruments within our framework, including a round-trip Tobin tax, which uniformly applies to both buyers and sellers, and a vector of tax or subsidy rates directly tailored to groups of investors playing different strategies such as buying to lease out or occupying as the owner.

We estimate our model using a major transfer tax reform in Taiwan which introduced surcharges of 15% on the sale price of non-owner occupied properties with a holding period under one year, 10% on sales with a holding period between one and two years, and no surcharge if the holding period exceeds two years. Two key aspects of this reform motivate our focus on it. One is that unlike many similar tax policies enacted elsewhere, the regime remains in place for several years without continuous tweaking of the tax schedule, allowing us to cleanly identify pre-reform and post-reform periods and focus on steady state effects of a discrete change in transfer tax rates. The second is that our access to administrative income and property tax records enables us to exactly compute individuals' tax liabilities and calibrate optimal transfer taxes targeting specific types of housing investors. The policy counterfactuals we consider closely correspond to most tax regimes where the statutory incidence disproportionately falls on home sellers.

Our theoretical approach extends the environment of Dávila (2022), who derives the optimal financial transaction tax when investors are indexed by their beliefs about asset fundamentals, and policymakers want to improve price efficiency by taxing away noise trading (à la Pigou). This framework, in turn, builds on Tobin tax experiments conducted in Scheinkman & Xiong (2003) and Vives (2017). In this class of models, whether prices go up or down depends on investors' prior beliefs and the relative impacts of the tax on supply and demand for the asset. Even if asset supply is perfectly inelastic, transaction taxes have competing effects on demand; if the tax is successful at crowding out traders with incorrect beliefs, then price efficiency improves, which may bid up asset demand.

We show how implementing the optimal uniform tax entails setting aggregate trading volume equal to fundamental volume, implying a tax rate which scales the *ex ante* share of non-fundamental trading by the semi-elasticity of volume with respect to the transfer tax rate. These are the two sufficient statistics we target in our empirical research designs. We recover sufficient statistics formulas similar to those derived in Dávila (2022) for a general risky asset paying a common dividend, even when we allow for housing tenure decisions and a more complex risk structure in which investors are exposed to both pricing (capital gain) and rental income (dividend) risk. Further, our optimal tax analysis reflects the observation in Sinai & Souleles (2005) that renting is risky, and investors with non-owner occupied properties – who are the primary target of transfer taxes in practice – are exposed to rental income risk through renters' substitution towards homeownership when rents fluctuate.

Linking the universe of personal income tax returns to property registrations and transfer tax records, we estimate the key empirical moments needed to calibrate our optimal flip tax model. The tax was very effective at reducing the number of property flips, inducing a 75% drop in one-year flips, and a 40% drop in overall sales volume. We estimate an upper bound of a 20% share of noise trading in the second home market prior to the transfer tax reform. We use our noise trading share and crowd out measures as sufficient statistics to compute an upper-bound optimal tax rate on flips of 3.90%, which is comparable to the flat transfer tax rates imposed in many global real estate markets.

As an alternative to the sufficient statistics approach, we adopt a price-rent ratio target to calibrate the more realistic version of our model which allows for separate taxes on landlord-sellers (flippers), landlord-buyers, and renter-buyers. For example, for a policymaker committed to achieving a moderate price-rent ratio of 20, we estimate optimal tax rates of 4.97%, −1.32%, and 3.10%, respectively, or a weighted-average optimal tax rate of 4.35%. Intuitively, we find the optimal tax on flippers is lower and implicit subsidies to new homeowners are less generous when the planner's desired price-rent ratio is higher. The overall housing price level increases in a convex fashion with higher taxes on flippers, but the price-rent ratio falls, and owning becomes *relatively* more affordable than renting. For all price-rent ratio targets, renters on the margin of homeownership realize large welfare gains at the expense of flippers under optimal taxation compared to the pre-existing tax regime.

Policymakers enact Tobin taxes with the hope of "cooling" the market, but our model counterfactuals cast doubt on this possibility and point to an increasing, convex relationship between equilibrium prices and the tax rate on property flips. Our model with type-targeted Tobin taxes fitted to the pre-reform data predicts that prices increase after the transfer tax hike. We empirically document that quality-adjusted prices rose after the reform, driven by spillovers to the untreated owner-occupied segment of the market and by the prime property segment where prices rose by 10% around the date cutoff. These positive pricing effects accord with the theory of Piazzesi, Schneider, & Stroebel (2020), where investors with preferences for low-inventory properties dampen negative demand shocks to other market segments.

The real estate transfer taxes we analyze share several features with financial transaction taxes (FTTs), which have received renewed attention among policymakers in Europe since the Global Financial Crisis (Biais & Rochet 2022). Tobin (1978) famously introduced the idea of using FTTs to curb excess volatility arising from non-fundamental trading. Early evidence on whether Tobin taxes accomplish this objective is mixed. Umlauf (1993), Jones & Seguin (1997), and Hau (2006) all note that increased transaction costs are associated with lower trading volume but increased price volatility in Swedish, U.K., and French equity markets, respectively. We find, within one year of the reform, an 8% decline in volatility of per square-meter second home prices (3% decline for all home prices) driven by a 25% drop in volatility in the prime property segment. Our finding that the transfer tax generated large lock-in effects mirrors more recent studies of equity markets which highlight reductions in asset liquidity as a key determinant of the overall pricing effects of FTTs (Foucault, Sraer, & Thesmar 2011; Colliard & Hoffmann 2017; Deng, Liu, & Wei 2018).

A notable feature of anti-speculation housing transfer taxes, like the one we study, is that discontinuities, or "notches," in the tax schedule are often delineated by the *holding period* of the property. This is in contrast to several papers on broad-based transaction taxes which have all uncovered bunching around home sale price notches (Besley, Meads, & Surico 2014; Kopczuk & Munroe 2015; Slemrod, Weber, & Shan 2017; Best & Kleven 2018). The tax we study in our empirical application incentivizes traders to hold onto a property for at least two years, at which point the tax surcharge rate jumps down to 0%. The fact that discontinuities in the transfer tax are defined in units of time presents a challenge when it comes to identifying an appropriate counterfactual to quantify changes in sales volume due to the tax.[1] The standard approach in the bunching literature is to use local polynomial regressions to fit a counterfactual distribution, using data from segments of the housing

[1]This emphasis on short-term trading is also a feature of capital gains taxes, which apply lower rates to long-term investments, and like transfer taxes, induce lock-in effects (Auerbach 1988; Burman & Randolph 1994; Cunningham & Engelhardt 2008; Dai et al. 2008; Gao, Sockin, & Xiong 2020).

market which are located away from discontinuities in the tax schedule (Kleven & Waseem 2013; Kleven 2016; Glogowsky 2021). But a property owner's decision to sell today has a mechanical and direct effect on the mass of sales at longer holding period lengths, meaning there is no "unaffected region" of the post-reform holding period distribution.

We propose an hedonic-logit model of house flips which we train on data from the pre-reform period. We then apply the factor loadings from this model to the post-reform period to estimate a counterfactual which adjusts for compositional changes over time which may have been due to the tax reform, macroeconomic factors, or changes in preferences. Our identifying assumption is that the market would have priced property amenities in the same fashion as in the pre-reform period in the absence of the tax. We test this by confirming the absence of pre-trends on the loadings for factors included in our hedonic-logit model.

Our study contributes to the recent body of evidence that property investors magnify real estate cycles. Chinco & Mayer (2016) show that demand from out-of-town (OOT) buyers predicts house price appreciation in the 2000s U.S. Sales involving OOT buyers account for one-third of transactions, but 60% of missing sales derived from our bunching analysis, indicating that the transfer tax essentially targeted this group. The positive pricing effects of the "OOT shock" to local housing markets have been echoed in the U.K. (Sá 2016; Badarinza & Ramadorai 2018), Paris (Cvijanović & Spaenjers 2021), Vancouver (Pavlov & Somerville 2020), and in large U.S. markets like California (Li, Shen, & Zhang 2018) and New York (Suher 2016). Gorback & Keys (2020) argue that a more recent wave of stamp duty taxes on non-residents in Singapore (Deng, Tu, & Zhang 2019), Hong Kong (Agarwal et al. 2022), and Australia (Hartley et al. 2021) drove up prices in the U.S. by generating an influx of Chinese capital into major U.S. real estate markets.

Our results add nuance to the narrative of the novice investor who buys several bottom-tier properties and earns low returns (e.g. Haughwout et al. 2011; Chinco & Mayer 2016). The richness of our transactions records linked to personal income tax returns and wealth statements allows us to move beyond capital gains and compute total *tax-adjusted* holding period returns, which include mortgage interest payments and rental income. While OOT and low-wealth investors account for an outsize share of property flips that were crowded out by the transfer tax, short-term speculators *do not* appear to be misinformed. Locals and OOT sellers earned statistically similar returns even after the tax reform, and leveraged property investors earned capital gains similar to those of full equity holders. Hence, as described in Bayer et al. (2020), tags like non-residency status and leverage which are synonymous with housing speculation in the literature may not necessarily translate to noise trading.

Given these facts about heterogeneous returns, we compute the optimal uniform flip tax rate by combining our estimates of the reduction in trading volume from our bunching design with new estimates of the noise trading share in the second home market. We exploit spatial and time variation in severe weather during typhoon seasons in the pre-reform period as a shock to the fixed cost of selling second homes. Our use of weather shocks is inspired by Cho (2021), who documents heat waves in the 19th century reduced noise trading on the NYSE. In recognizing that weather conditions may increase fixed costs of selling properties, we build upon an emerging finance literature which has so far focused on the relationship between weather-induced sentiments and economic activity (Hirshleifer & Shumway 2003; Goetzmann et al. 2014; Cortés, Duchin, & Sosyura 2016; Dehaan, Madsen, & Piotroski 2017).

Tropical storm-level rainfall events generate a robust 20% drop in aggregate sales volume that does not immediately rebound once the rainy season ends, which yields an upper-bound estimate for the noise trading share of 20%. Reassuringly, we estimate similar drops in local sales volume and a lack of pent-up demand when we match properties to documented tropical storm pathways to exploit more granular variation in severe weather conditions. As a further sanity check, when we condition on common tags for noise trading such as non-resident status, transactions not occurring around marital status or employment changes, or short holding periods, we find a 15 p.p. reduction in the share of trades satisfying these criteria during days with tropical storm levels of precipitation. We confirm via high-frequency event study analysis that this is not simply due to noise traders intertemporally shifting transactions forward or backward in response to weather forecasts or official storm warnings.

We formally embed the relationship between weather conditions and noise trading into our framework by introducing search costs. We model these costs as arising from a combination of investors' potentially biased beliefs about the ease of buyer-seller matching, and persistent shocks which mimic the slow recovery of housing sales volume we document following a severe storm. One might argue that inclement weather reduces sales volume through two mechanisms: by deterring buyers with noisy beliefs but also by increasing fixed transaction costs for all agents. We show in our augmented model that the magnitude of the latter channel is proportional to search costs as a fraction of housing prices. When we parameterize this search cost using time on the market as a measure of liquidity, we find that it is quantitatively small, indicating that the optimal flat tax rate from our original sufficient statistics formula is biased upward by, at most, 0.22 p.p.

Finally, we address macroprudential considerations policymakers often invoke to support real estate transaction taxes. Like us, Kaplan, Mitman, & Violante (2020) emphasize the role of shifts in beliefs about future housing demand, rather than credit conditions, in driving housing cycles. The Taiwan transfer tax reform occurs during a period of rising levels of mortgage debt and price-rent ratios, and, as argued in Koetter, Marek, & Mavropoulos (2021), transfer tax hikes operate as leverage limits by effectively reducing buyers' maximum loan-to-value ratio. Favilukis & Van Nieuwerburgh (2021) use a mono-city model to study the effects of OOT investors in general equilibrium and find that targeted transfer tax hikes are welfare-improving. DeFusco, Nathanson, & Zwick (2022) build a model with short-term and long-term investors with extrapolative beliefs, and conclude that short-term capital gains taxes on real estate sales promote financial stability. Our work provides a real-world laboratory to test whether property flip taxes can mitigate bubbles by deterring noise trading.

The paper proceeds as follows. Section 2 introduces the structural framework underlying our optimal flip tax analysis. Section 3 provides background on our data and empirical setting. Section 4 presents our main estimates of quantity responses to the Taiwan flip tax reform. Section 5 characterizes short-term property investors by their returns and offers strategies for identifying noise trading. Section 6 combines our sufficient statistics estimates to back out the optimal uniform Tobin tax on housing and discusses the distributional implications of transfer taxes targeted towards investor types. Section 7 concludes.

2 Optimal Real Estate Transfer Tax Framework

This section presents a simple two-period equilibrium model with heterogeneous investors who disagree on the fundamental value of housing. Renters and homeowners are differentially exposed to rental and housing price risks. We first introduce a baseline version of the model in which the policymaker implements the second-best allocation by levying a linear round-trip transfer tax which applies uniformly to all investors. The planner cares about achieving price efficiency in this market, so the optimal linear Tobin tax functions as a Pigouvian tax on pecuniary externalities. The optimal rate eliminates any spread between the average expected returns of buyers and sellers of housing.

Our baseline model yields a sufficient statistics formula that we apply to the housing transfer tax reform targeting speculators in our empirical setting. We then examine the more realistic case of a policymaker who conditions on investor characteristics to set group-specific taxes, such as separate taxes on second homeowners, renters, and owner-occupiers. We offer model extensions in Appendix A to bring the framework closer to actual policy settings.

2.1 Baseline Framework: Uniform Tobin Tax Instrument

We consider a two-period heterogeneous investor environment with housing as a risky asset, which carries an additional consumption cost H. The value of this housing cost depends on whether households are one of three types: renters, owner-occupiers, or landlords. Investors consume housing services on a continuous scale X, which refers to total floor space (e.g. square meters or square feet) occupied. We center this floor space scale around unity so that renters correspond to investors i who use $X_i < 1$, owner-occupiers use exactly $X_i = 1$, and landlords use $X_i > 1$. In other words, landlords occupy $X_i = 1$ themselves, and rent out any surplus floor space $X_i - 1$ at the prevailing rental rate r.[2]

There is a unit mass of investors indexed by i and distributed via cumulative distribution function $F(\cdot)$ such that $\int dF(i) = 1$. Investors make their housing decisions in period 1 and consume in period 2. All investors maximize expected utility with constant absolute risk aversion coefficient A_i, which varies across investors:

$$\mathbb{E}_i[U_i(C_{i,2})] = \mathbb{E}_i\Big[-\exp(-A_i \cdot C_{i,2})\Big] \tag{2.1}$$

where $C_{i,2}$ refers to terminal (or lifetime) housing consumption net of any taxes, transfers, or housing costs. Implicit in equation (2.1) is that investors liquidate and consume all terminal housing wealth. Expectations are indexed by i, since investors hold heterogeneous beliefs about rents and housing prices, which we will describe shortly.

There is a risk-free asset in elastic supply which offers a gross interest rate normalized to 1. We assume housing is in exogenously fixed supply $Q \geq 0$. $X_{i,0}$ is the initial asset endowment, which in this case indicates how much housing an investor is "born" with or inherits. Housing endowments must add up to total housing supply Q, so $\int X_{i,0} dF(i) = Q$. We assume investors' housing decisions are not subject to borrowing constraints, so any loan-to-value (LTV) or debt-to-income (DTI) limits do not bind. We discuss the possibility of leverage limits as a complementary policy tool to housing Tobin taxes in Section 6.[3]

For now we assume the planner has access to a single policy instrument in the form of a linear housing transaction tax τ, levied as a surcharge on the price of any housing sold in period 1. This tax applies uniformly to both buyers and sellers, and is in that sense a "round-trip" tax like the one proposed by Tobin (1978). We are not aware of any existing anti-speculator housing transfer tax schemes which were levied to meet revenue constraints or

[2] Our quantitative optimal tax conclusions carryover to a discrete calibration of this model where investors demand an integer-valued number of houses X. We obtain optimal tax rates of similar magnitude regardless of whether we calibrate the model to continuous or discrete housing decisions, but in our main analysis we calibrate to a continuous housing scale for which objective functions are differentiable.

[3] In our empirical setting we do not observe any taxpayers with $X \leq 0$, but the baseline optimal uniform tax formula we obtain holds in the presence of short-selling constraints. Intuitively this is because short-sale constrained investors are inframarginal to changes in the tax rate (i.e. $dX_{i,1}/d\tau = 0$ for them). Our framework therefore can accommodate prohibitions on short selling, even without us directly imposing $X > 0$.

finance particular public goods, and so we assume that tax collections are rebated lump-sum to investors.[4] That is, each investor receives a rebate $T_{i,1}$ and the government runs a balanced budget: $\int T_{i,1} dF(i) = \int \tau \cdot P_1 |\Delta X_{i,1}| dF(i)$. Applying a uniform rebate rule, rather than an individually-targeted rebate which sets the rebate equal to the investor's tax liability, accounts for redistributive effects of taxing housing transactions.

Lifetime housing consumption is then given by the identity:

$$C_{i,2} = Y_{i,2} + P_2 \cdot X_{i,1} + P_1 \cdot (X_{i,0} - X_{i,1}) - \tau \cdot P_1 |\Delta X_{i,1}| + T_{i,1} - H_{i,2} \tag{2.2}$$

where $Y_{i,2}$ is the stochastic endowment (i.e. income). $P_1 \cdot (X_{i,0} - X_{i,1})$ captures proceeds from sales of initial asset holdings. Importantly, the housing cost in budget constraint (2.2) is stochastic and investor specific. We define this housing cost so that it captures imputed rents that landlords and owner-occupiers pay to themselves, and differential exposure to rental risk across the three main investor types:

$$H_{i,2} = (1 - X_{i,1}) \cdot r_2 \quad \text{with} \quad r_2 \sim_i N(\mu_i^r, (\sigma^r)^2) \tag{2.3}$$

We assume that the fundamentals of the economy are such that the per unit value of housing P_1 is always strictly positive. However, the unit value of housing in period 2 is stochastic and depends on investor beliefs: $P_2 \sim_i N(\mu_i^p, (\sigma^p)^2)$.

In this setting, the *ex post* return, or net dividend yield $\widetilde{D}/P_1$ accrued from occupying and/or renting out housing can then be expressed as:

$$R_{i,2} = \frac{P_2 - H_{i,2}}{P_1} = \frac{\widetilde{D}_i}{P_1} \tag{2.4}$$

wherein P_2/P_1 captures the per unit "capital gain" component to the return which is common across investors, and $H_{i,2}$ captures the housing cost which varies by investor type. By definition, renters choose $X_{i,1} < 1$, implying from (2.3) that housing costs enter negatively into their utility. Similarly, landlords choose $X_{i,1} > 1$, so housing costs enter positively into their utility, indicating that they receive a stream of rental income on the portion of their housing portfolio that they themselves do not occupy. Thus, by modeling the housing cost in this fashion, we incorporate the rental risk premium emphasized in Sinai & Souleles (2005) and investors' housing tenure decisions.

[4] Given the substantial lock-in effects of the transfer tax we find in Section 4, such taxes may not raise much revenue. Favilukis & Van Nieuwerburgh (2021) find in a two-city general equilibrium model that the use of transfer tax revenues towards public goods valued by residents can be important for aggregate welfare, but our focus here is on the use of transfer taxes as a way to correct price distortions under biased beliefs.

We now present the investor's maximization problem as choosing housing (floor space) demand $X_{i,1}$ under a linear tax imposed on transactions:

$$\max_{X_{i,1}} \left\{ \Big[\mu_i^p - P_1 - A_i \cdot Cov(Y_{i,2}, P_2)\Big] \cdot X_{i,1} - \tau \cdot P_1|\Delta X_{i,1}| - \frac{A_i}{2} \cdot (X_{i,1}\sigma^p)^2 + RP_i \right\} \tag{2.5}$$

$$RP_i = (1 - X_{i,1}) \cdot \Big[-\mu_i^r - \frac{A_i}{2}(1 - X_{i,1}) \cdot (\sigma^r)^2 + A_i \cdot Cov(Y_{i,2}, r_2) + A_i X_{i,1} \cdot Cov(P_2, r_2)\Big] \tag{2.6}$$

Implicit in this maximization problem is the assumption that landlord-sellers perfectly pass through the costs of the transfer tax to their tenants. One can easily generalize this to the incomplete pass through case by defining the tax burden as $\tau \cdot \xi \times \mathbb{1}\{X_{i,1} < 1\}$ for some constant $\xi < 1$.[5] In writing the maximization problem in this way, we emphasize that asset demand in the housing market depends on the risk premium RP_i that an investor is willing to pay to avoid any risk associated with renting. Asset price risk in (2.5) appears through the expected housing appreciation term: $(\mu_i^p - P_1) \cdot X_{i,1}$.

Given an initial price P_1 and positive flat tax rate $\tau > 0$, equilibrium net asset demand arising from this problem is therefore:

$$\Delta X_{i,1}(P_1) = \begin{cases} \Delta X_{i,1}^+(P_1) = \frac{(\mu_i^p + \mu_i^r) - A_i\Omega_i - P_1(1+\tau)}{A_i\Omega} - X_{i,0} & \text{if } \Delta X_{i,1}^+(P_1) > 0 \\ 0 & \text{if } \Delta X_{i,1}^+(P_1) \le 0, \Delta X_{i,1}^-(P_1) \ge 0 \\ \Delta X_{i,1}^-(P_1) = \frac{(\mu_i^p + \mu_i^r) - A_i\Omega_i - P_1(1-\tau)}{A_i\Omega} - X_{i,0} & \text{if } \Delta X_{i,1}^-(P_1) < 0 \end{cases} \tag{2.7}$$

where net asset demand is $X_{i,1}(P_1) - X_{i,0}$, and for shorthand we define the investor-specific and uniform variance-covariance terms, respectively, as Ω_i and Ω:

$$\Omega_i = \underbrace{Cov(Y_{i,2}, P_2) + Cov(Y_{i,2}, r_2)}_{\text{fundamental risk}} + \underbrace{Cov(P_2, r_2)}_{\text{affordability risk}} - (\sigma^r)^2 \tag{2.8}$$

$$\Omega = (\sigma^p)^2 + (\sigma^r)^2 - 2Cov(P_2, r_2) \tag{2.9}$$

Equation (2.7) shows that investors can be sorted into three main categories based on changes in their housing positions. Buyers expand their housing portfolio ($\Delta X_{i,1}^+(P_1) > 0$), while sellers scale back their holdings ($\Delta X_{i,1}^-(P_1) < 0$).

The covariance terms in (2.8) and (2.9) show how housing demands are determined by investors' needs to hedge against two sources of risk: (i) fundamental risk from the covariances of rents and prices with the investor's endowment $Y_{i,2}$, and (ii) *affordability risk* which

[5] In Appendix C, we discuss evidence from our application to the Taiwanese housing market of close to 100% pass through for high-end properties where transaction volume is concentrated.

is a market-wide factor captured by the covariance of prices with rents. The greater this covariance, the less renting or collecting rental income offers a hedge against house price movements.[6] Affordability risk is a key feature which distinguishes our theoretical setting from related models of FTTs imposed on trading equities. As we formalize in the next subsection, these two risks interact in different ways depending on housing tenure choices.

Trading volume is the sum of the asset demands from equation (2.7) over the set of buyers:

$$V(\tau) = \int_{i \in \mathcal{B}(\tau)} \Delta X_{i,1}(\tau) dF(i) \tag{2.10}$$

Imposing market clearing, $\int \Delta X_{i,1}(P_1) dF(i) = 0$, we can solve for the equilibrium price as an implicit function of risk preferences A_i and traders' risk exposure:

$$P_1 = \frac{\int_{i \in \mathcal{T}(P_1)} \left(\frac{(\mu_i^p + \mu_i^r)}{a_i} - A \left(\Omega_i + \Omega X_{0i} \right) \right) dF(i)}{1 + \tau \cdot \left(\int_{i \in \mathcal{B}(P_1)} \frac{1}{a_i} dF(i) - \int_{i \in \mathcal{S}(P_1)} \frac{1}{a_i} dF(i) \right)} \tag{2.11}$$

where $A \equiv (\int_{i \in \mathcal{T}(P_1)} A_i^{-1} dF(i))^{-1}$ is the harmonic mean of risk aversion coefficients across active traders, and $a_i = A_i / A$. We use the sets $\mathcal{T}$, $\mathcal{B}$, and $\mathcal{S}$ to denote investors who are traders, buyers, and sellers, respectively. Equation (2.11) is an implicit characterization of the equilibrium price, because the composition of these sets depends, in turn, on the price. From the numerator of (2.11), we observe that prices are increasing in the expected payoff to owning housing, or $\mu_i^p + \mu_i^r$. The second term in the numerator is proportional to the rental risk premium in (2.6), where A is the price of risk, and the quantity of risk originates from the variance-covariance terms in (2.8) and (2.9), scaled by portfolio exposure $X_{i,0}$.[7]

Having characterized the equilibrium in this market, we are now ready to derive an expression for the optimal Tobin tax rate. The policymaker chooses τ to maximize the sum of investors' certainty equivalents. The investor's certainty equivalent from the planner's perspective is given by:

$$CE_i^p(\tau) = \left[(\mu_p^p + \mu_p^r) - P_1 - \Omega_i \right] \cdot X_{i,1}(\tau) + P_1(\tau) \cdot X_{i,0} - \frac{A_i}{2} \Omega \cdot (X_{i,1}(\tau))^2 + \widetilde{T}_{i,1}(\tau) - \mu_p^r \tag{2.12}$$

[6] Holding the equilibrium price P_1 fixed, affordability risk has a negative effect on housing demand, or $\partial X_{i,1} / \partial Cov(P_2, r_2) = -3A_i < 0$.

[7] In general, the sign of $dP_1/d\tau$ is ambiguous from the standpoint of the model. We elaborate on the conditions under which Tobin taxes increase or decrease the equilibrium price of housing in Appendix A.1.

where $\widetilde{T}_{i,1}(\tau) = T_{i,1}(\tau) - \tau \cdot P_1(\tau)|\Delta X_{i,1}(\tau)|$ is the transfer the investor receives net of any tax burden they face. μ_p^p and μ_p^r reflect the planner's beliefs on prices and rents, respectively. The planner sets the transfer rule $T_{i,1}(\tau)$. The aggregate certainty equivalent is:

$$CE^p(\tau) = \int CE_i^p(\tau)dF(i) \tag{2.13}$$

and the optimal linear tax satisfies $\tau^* = \text{argmax}_\tau CE^p(\tau)$. The individual marginal welfare impact of τ maximizes the aggregate certainty equivalent:

$$\begin{aligned}\frac{dCE_i^p}{d\tau} &= \Big[(\mu_p^p + \mu_p^r) - (\mu_i^p + \mu_i^r) + sgn(\Delta X_{i,1}(\tau)) \cdot P_1(\tau) \cdot \tau\Big]\frac{dX_{i,1}(\tau)}{d\tau} \\ &- \Delta X_{i,1}(\tau) \cdot \frac{dP_1(\tau)}{d\tau} + \frac{d\widetilde{T}_{i,1}(\tau)}{d\tau}\end{aligned} \tag{2.14}$$

where the gap between the planner and investor beliefs on the expected payoff from housing is $(\mu_p^p + \mu_p^r) - (\mu_i^p + \mu_i^r)$. This leads to the following lemma.

Lemma 1. *(Tax equivalence) The sufficient statistics formula for the optimal linear financial transaction tax is equivalent to that in Dávila (2021):*

$$\tau^* = \frac{s_{NF}\{\tau = 0\}}{\frac{-d\log V}{d\tau}\Big|_{\tau=0}} \tag{2.15}$$

Even after incorporating a richer market microstructure in which there is both pricing and dividend risk and owners and renters, we recover a familiar sufficient statistics formula when housing is taxed as if it were a financial asset. This formula says that, starting at a zero transfer tax rate, the optimal tax rate is the fraction of non-fundamental investors in this market, denoted by s_{NF} scaled by the semi-elasticity of sales volume with respect to the tax.[8] Tenure choices affecting future housing costs will not change the optimal flat tax rate.

Like all optimal tax formulas in public finance, equation (2.15) showcases a tradeoff. There is more scope for a tax to improve price efficiency if the pre-existing share of non-fundamental trading $s_{NF}\{\tau = 0\}$ is large. However, welfare gains to imposing the tax are limited by the extent to which the tax deters fundamental trades, captured by the semi-elasticity of volume with respect to the tax in the denominator. Our bunching analysis in Section 4.2 calibrates this semi-elasticity, but as our facts about return heterogeneity presented in Section 5.1 indicate, relying on observable tags such as non-residency or leverage is not sufficient to

[8] The formula in (2.15) corresponds to Proposition 2 in Dávila (2021). We derive expressions for fundamental and non-fundamental trading shares in Appendix A.1.

identify noise traders. This leads us to instead use severe weather shocks to tease out the *ex ante* noisiness of the market for investment properties.

To preview our calibration results, we estimate a volume semi-elasticity (the denominator) of -5, and an *ex ante* noise trading share of 20% (the numerator), which implies an optimal flat tax rate of 4%. In Section 6, we put bounds on our optimal tax estimates and discuss the redistributive implications of housing transfer taxes. As the policy background we provide in Appendix B demonstrates, an optimal flat tax rate of 4% is at the upper end of tax rates that have been implemented in the top 25 global housing markets.

2.2 Setting Investor-Specific Optimal Tax Rates

We now suppose that policymakers can set investor-specific (linear) taxes. Tenure choices are determined by investors' beliefs on rents and prices, and thus the policymaker relies on targeted taxes on renters and landlords to implement the first-best allocation. We can categorize investors in this market into four groups based on their housing demand:

$$\begin{cases} X^{-}_{i,1}(\tau'_i) < X_{i,0} \leq 1 & \text{renter-seller (RS)} \\ \max\{1, X^{-}_{i,1}(\tau'_i)\} < X_{i,0} & \text{landlord-seller (LS)} \\ X_{i,0} \leq \max\{1, X^{+}_{i,1}(\tau'_i)\} & \text{renter-buyer (RB)} \\ 1 < X_{i,0} < X^{+}_{i,1}(\tau'_i) & \text{landlord-buyer (LB)} \end{cases} \tag{2.16}$$

The initial asset endowment $X_{i,0}$ sorts investors into renters and landlords, while heterogeneous beliefs about rents and prices, hedging needs captured by the covariance of the income endowment with rental and pricing risk, and taxes determine whether households are sellers, buyers, or inactive investors ($\Delta X_{i,1} = 0$).[9] If initial holdings and beliefs are the only sources of heterogeneity, then landlord-buyers must be more optimistic than renters.[10]

Optimal taxes targeting individual investors are given by:

$$\tau^*_i = \frac{sgn(\Delta X_{i,1}) \cdot (\mu^p_i + \mu^r_i - \Upsilon)}{P^*} \tag{2.17}$$

[9] An investor who demands $X_{i,1} = 1$ is strictly an owner-occupier. There is a zero mass of investors at this housing demand level, and such investors would be risk neutral with respect to rental risk. Ignoring this investor type is without loss of generality if investors who are initially owner-occupiers remain owner-occupiers regardless of the tax rate. Such is the case when transfer taxes apply to second homeowners. Our calibration results in Section 6 support a hefty tax on landlord-sellers and more modest tax rates on other groups.

[10] A "renter-seller" in this scenario is a renter who lowers their demand for floor space, while a "renter-buyer" is a renter who increases their demand for floor space, but not to such an extent that $X^+ \geq 1$.

where Υ is any real number, and P^* is the market-clearing price in period 1, which satisfies $\int \Delta X_{i,1}(P^*)dF(i) = 0$. In Section 6, we calibrate the free parameter Υ to be the sum of mean observed prices and rents, or $\Upsilon \equiv \mu_p^p + \mu_p^r$. This is equivalent to assuming a production economy in which investors own the developers who supply housing units to the market.

Equation (2.17) says buyers who are more optimistic about future rents and prices pay a higher tax rate, and sellers who are more optimistic receive a lower subsidy if the optimal tax is negative. Assuming households are homogeneous within each of the two groups of sellers, the gap between the optimal tax on a landlord-seller vs. a renter-seller is equal to the gap in beliefs on prices and rents, relative to the current equilibrium price, or

$$\tau_{LS}^* - \tau_{RS}^* = \frac{(\mu_{RS}^p + \mu_{RS}^r) - (\mu_{LS}^p + \mu_{LS}^r)}{P^*} \tag{2.18}$$

where μ_g^p and μ_g^r are beliefs about future housing prices and rents for investors in one of the groups $g \in \{RS, LS, RB, LB\}$ sorted by asset demand in (2.16).

Our model implies the following regression relating housing demand and hedging needs to movements in prices and investor-specific tax rates:

$$\widehat{\Omega} \cdot X_{i,t} + \widehat{\Omega}_i = \alpha_i \cdot P_t \times (1 + \mathcal{D}_{i,t} \cdot \tau_{i,t}) + e_i \tag{2.19}$$

$$\text{where} \qquad \mathcal{D}_{i,t} = \begin{cases} -1 & \text{if } X_{i,t} < X_{i,t-1} \quad \text{(sellers)} \\ 1 & \text{if } X_{i,t} > X_{i,t-1} \quad \text{(buyers)} \end{cases}$$

For shorthand, we define $\alpha_i = -1/\widehat{A}_i$, and $(\widehat{\mu_i^p} + \widehat{\mu_i^r}) = -e_i/\alpha_i$. $\tau_{i,t}$ is the effective transfer tax rate that investor i faces under the current tax code.[11] The regression in equation (2.19) relates investors' hedging needs on the LHS to individual risk preferences α_i and exposure to tax liability $P_t \cdot \tau_{i,t}$, which may differ across buyers and sellers. The hypothetical housing demand of investor i under the optimal tax rate can then be written as:

$$X_{i,1}(\tau_i^*) = \frac{-A_i \cdot \Omega_i - P^* + \Upsilon}{A_i \cdot \Omega} \tag{2.20}$$

which is not a function of unobservable beliefs. Analogously, the estimated housing position is $\widehat{X}_i$, and takes as inputs estimates of the constant absolute risk aversion coefficient from the

[11] As we describe in Appendix B, in our empirical application this effective tax rate includes the surcharge reform on sellers, as well as deed and stamp duty tax rates levied on both buyers and sellers.

regression in (2.19) and the estimated market-clearing price $\widehat{P}$, which satisfies the condition:

$$\sum_i \Delta \widehat{X}_i = \sum_i \Delta \left\{ \frac{-\widehat{A}_i \cdot \widehat{\Omega}_i - \widehat{P} + \Upsilon}{\widehat{A}_i \cdot \widehat{\Omega}} \right\} = 0 \tag{2.21}$$

Assuming that individual tax liability is fully rebated via lump-sum transfers, the counterfactual welfare loss of group g in period t is given by the difference between the aggregate group certainty equivalents under the counterfactual optimal tax regime τ_g^* and the actual tax regime τ_g:

$$\Delta \mathcal{W}_{g,t} = \left\{ \left[(\widehat{\mu}_g^p + \widehat{\mu}_g^r) - \widehat{P} - \widehat{\Omega}_g \right] \widehat{X}_g + \widehat{P} X_{t-1,g} - \tfrac{\widehat{A}_g}{2} \widehat{\Omega} \left(\widehat{X}_g \right)^2 \right\} - \left\{ \left[(\widehat{\mu}_g^p + \widehat{\mu}_g^r) - P_t - \widehat{\Omega}_g \right] X_{t,g} + P_t X_{t-1,g} - \tfrac{\widehat{A}_g}{2} \widehat{\Omega} \left(X_{t,g} \right)^2 \right\} \tag{2.22}$$

$P_t, X_{g,t-1}, X_{g,t}$ refer to actual prices, pre-reform and post-reform property holdings, respectively. $\widehat{\Omega}_g$ is the group-specific analog of (2.8), which varies across groups according to the covariance of income endowments with rents and prices. The aggregate welfare loss is the share-weighted average of the welfare losses across investor groups.

While the optimal uniform tax is independent of policymakers' beliefs about rents and prices, the same cannot be said of type-specific optimal taxes and aggregate welfare, both of which are functions of μ_p^p and μ_p^r. We thus need to calibrate the optimal non-uniform tax by choosing a price-rent ratio target, μ_p^p/μ_p^r, a common metric for gauging the success of macroprudential housing policy (He, Nier, & Kang 2016; Gilbukh, Haughwout, & Tracy 2017). We explore how the vector of optimal tax rates varies with this policy target in Section 6, with the key finding that attaining a lower price-rent ratio requires a higher tax on flippers.

We calibrate investor type-specific tax rates to rich administrative data containing housing portfolios and individuals' tax liabilities. The calibration involves estimating the regression in (2.19). We defer a more complete discussion of our procedures to Section 6.2, but preview our findings by noting that for a price-rent ratio target of 20 – a common heuristic cutoff for bubbly housing markets – the vector of optimal tax rates includes a tax on landlord-sellers (i.e. the flippers) of 4.97%, a subsidy to landlord-buyers of −1.32%, and a tax on renter-buyers of 3.10%. For all price-rent ratio targets, renter-buyers realize large welfare gains at the expense of flippers under optimal taxation compared to the pre-existing tax regime.

In Appendix A.1 and Appendix A.2 we derive optimal tax formulas in the presence of housing search costs and persistent trading frictions. Our baseline model does not differentiate investors based on their housing investment horizon. In Appendix A.3, we incorporate discount rate heterogeneity into our framework to formalize the link between flips and noisy transaction volume. We do this while retaining the empirical tractability of our static two-period environment. We then propose an empirical decomposition using expected returns and based on an alternative derivation of the optimal Tobin tax to quantify how heterogeneity in investment horizon contributes to pricing inefficiencies above and beyond those generated by investors trading based on biased beliefs about fundamentals. We conclude incorrect pricing beliefs alone account for about 87% of the optimal tax rate, while heterogeneity in investment horizon accounts for the remaining 13% (or, 0.6 p.p.). The planner learns little additional information about the extent of pricing inefficiency from discounting, conditional on knowing the distribution of biased beliefs about property values.

3 Policy Background & Data

This section offers an overview of the Taiwan transfer tax reform we use as the empirical setting to calibrate our model of optimal housing Tobin taxes. We then describe how we link property transactions data to personal income and property tax returns. In Appendix B, we compare Taiwan's tax regime to that of other major real estate markets.

3.1 Taiwan's Real Estate Transfer Tax

Housing prices in Taiwan dramatically increased after the onset of the Global Financial Crisis in 2008. Figure 1 plots the time series of quality-adjusted housing price levels for Taiwan's six major cities and price-rent ratios for the capital region including Taipei and New Taipei. Prices in the largest housing market of New Taipei rose by 60% (41% in real terms) from 2001Q1 to 2011Q1, with 32 p.p. of this increase occurring in the two years between 2009Q1 and 2011Q1. Over the same time, New Taipei's price-rent ratio rose from 18 to 30, prompting concerns from policymakers about an impending housing affordability crisis.[12]

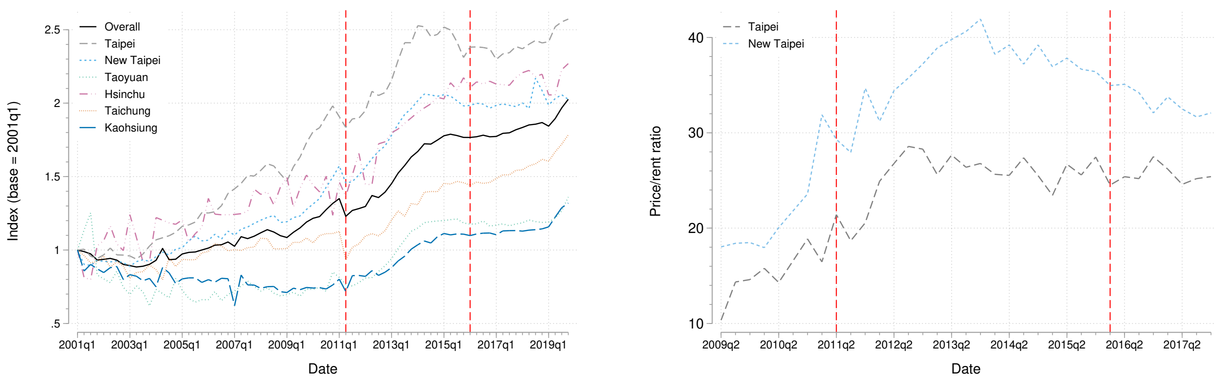
Attributing this house price appreciation to an increase in property flips, the government announced in January 2011 the passage of a transfer tax surcharge (TTS) on short-term sales of non-owner occupied properties, effective on June 1, 2011.[13] Under the new law, sellers were required to pay a fraction τ of the sale price according to the following rate schedule: 15% on

[12]Publicly available indices do not show any dip in price levels after the transfer tax reform. Our index in Figure 1 implies a 7% decline in aggregate housing price levels within a quarter of the reform. The reason for the discrepancy is that extant price indices exclude sales within a six month holding period.

[13]The official name for the policy is the Specifically Selected Goods and Services Tax. According to the Ministry of Finance website, the stated purpose of the tax was "to achieve a well-functioning housing market with fair taxes that satisfy societal expectations." The surcharge also applies to self-reported transfers of special categories of goods, such as passenger vehicles valued at more than 3 million NTD.

FIGURE 1. Quarterly Housing Price Levels and Price-Rent Ratios

A. Price Indices for Top Six Markets B. Price-Rent Ratios for Taipei/New Taipei



Notes: Panel A of the figure plots our housing price indices created using the matching estimator method to compute quality-adjusted price levels. We discuss this method in detail in Appendix C. All indices normalized to unity in the base period of 2001Q1. Panel B plots the price-rent ratio for the two largest cities of Taipei and New Taipei, for both of which we can create a consistent sample of contract rents covering the period 2009Q2 to 2017Q4. Following standard practice, we compute the price-rent ratio as the median house price divided by the median annual rent within each quarter. All prices and rents on a per square meter basis. Vertical red dashed lines indicate the transfer tax reform in 2011Q2 and a capital gains tax reform later implemented in 2016Q1, which replaced the earlier policy.

transactions with a holding period less than 1 year long, 10% on transactions with a holding period at or above 1 year but less than 2 years in length, and 0% for holding periods longer than 2 years. For calculating tax bill, the holding period is measured as the time elapsed between the seller's original purchase date and the sale date. Under these rules, owners of investment properties are incentivized to wait until at least two years before reselling.

This surcharge only applies to arms-length transactions; gifts between family members, transfers involving employers and their employees, or transfers of government properties are exempt, and we thus exclude such transactions from our analysis. For newly built properties, only the value of land transferred is subject to the surcharge. We drop transactions involving only new constructions or properties which underwent major renovations because the holding period is undefined in these cases.[14]

The transfer tax surcharge is large relative to payments required under other provisions of the property tax system. Important for our purposes, the June 2011 reform only added the surcharge to short-term sales. Other pre-existing provisions in the property tax code include

[14]The transfer tax incentivizes landowners to engage in property development prior to selling when the cost of development is less than the implied tax savings from reducing τ to zero. Despite this potential tax avoidance opportunity, we do not observe any spike in the number of transactions involving "unregistered partitions" (i.e. renovations) or newly built properties during the reform period.

six additional taxes – two imposed on buyers and four on sellers – which we describe in Appendix B. Since the surcharge rate directly applies to gross transfer income, for short-term sales it accounts for an outsize fraction of the total transfer tax payment due.[15]

The flip tax regime remained in place from June 1, 2011 until December 31, 2015. A key advantage to using Taiwan as our environment is that the transfer tax stays in place continuously over 4.5 years, so general equilibrium effects of stacking up multiple tax reforms and seasonality in windows around short-duration reforms do not play a role in our estimates. Importantly, the stable nature of the tax regime over our sample period allows us to map to the steady state equilibria in our structural model.[16]

3.2 Personal Income Tax & Property Data

We combine four main confidential tax datasets made available to us by the Financial Information Agency of the Ministry of Finance for years 2006 to 2016. We then merge the tax records to a registry of public property sales that we compiled from county offices.

Deed tax records. These data contain transaction dates, buyer and seller identifiers, and taxes paid by the buyer on the appraised property value, which we use to link property owners to their personal income tax returns and other files estimating taxpayer wealth. These data distinguish unique properties, so together with the transaction date, we can compute holding periods between sales for the 43% of observations where the previous sale date falls within our sample period. The files classify sellers and buyers based on their institutional and residency status. We also observe whether buyer-seller pairs share an employer, school, or other institutional affiliation. We use these markers to exclude non-arms-length transactions, sales involving a public entity, and probate transfers, as such sales may not reflect market conditions and are not subject to the transfer tax surcharge.

Building property tax records. We use the unique property identifiers in the deed tax data to link transactions to information on property characteristics – such as address, building material, zoning, use category (e.g. residential, commercial, industrial), number of floors, layout, area, and floor space, among other features – contained in the building property tax records. These records are collected annually, while building characteristics are updated every three years when an appraisal occurs. Because the building property tax rate depends

[15]Relabeling a second home as an owner-occupied unit would be an infeasible evasion strategy, as applications for permanent address changes would take at least a full tax year to be approved and processed.

[16]On January 1, 2016, the government replaced the surcharge with a capital gains tax where the rates are decreasing in holding period length, with higher rates of up to 45% imposed on non-resident sellers. In unreported results, we find no clear discontinuities in pricing around the implementation of the 2016 reform.

on the number of houses owned by the taxpayer and owner-occupied status of the structure, we combine the previous holding period with these records to identify sales subject to the transfer tax surcharge. We find 28% of taxpayers own more than one home.

Personal income tax returns. Our third dataset consists of the universe of personal income tax returns which we link to property owners via the same taxpayer ID listed in the property tax records. Taxpayers provide two addresses when they file income taxes: a contact address (i.e. the tax bill address) and an address used to determine residency and any local components of income tax liability. Following Chinco & Mayer (2016), we define out-of-town (OOT) buyers or sellers as taxpayers with a residency address outside one of the 22 administrative regions where the transacted property is located.[17] Given this definition, 73% of sales involve at least one OOT counterparty; sales where both the seller and buyer are OOT account for 27% of all arms-length transactions over our sample time period.

Income tax returns in Taiwan contain information on wages and salaries, as well as special sources of income such as lottery income and inheritances. Taxpayers also record interest payments towards mortgages, rental income and certain types of deductions for losses, donations, and insurance premia. We use the information on interest payments to adjust for net-of-tax mortgage payments in our definition of holding period returns in Section 5.1.

Personal wealth estimates. We use personal wealth records created by the government from a combination of property registrations and information reported by taxpayers on income tax returns, as described in Chu, Lin, & Liu (2017). We observe estimated values of properties, vehicles, equities, and savings and other liquid wealth. For vehicles, the tax authority uses information from DMV registrations to assign an average retail price for the make and model (including foreign and luxury vehicles), and subtracts linear depreciation. We compute savings deposits and other liquid wealth such as corporate bonds from interest income items in personal tax returns. To value stock shares we price non-publicly traded stocks at face value and price publicly-traded stocks at the closing price of the annual ex-right date.[18]

Housing sale prices and contract rents. Property sale values were not collected by the Ministry of Finance prior to the TTS reform in 2011, during which time transaction records were scattered across 109 local land offices. We collect these records and append them to the public transaction data which cover all regional markets beginning in 2012Q3. We merge the public transaction records to the confidential property and deeds tax data using the address

[17]Administrative regions are roughly equivalent in size to U.S. combined statistical areas (CSAs).

[18]For companies that do not distribute dividends, there is no ex-right date. In such cases we use the closing price on July 31 of each year.

string, latitude/longitude coordinates, and transaction dates. To compute the price-rent ratios pictured in Figure 1, we rely on a property-level survey of contract rents with consistent coverage of the Taipei-New Taipei area during our sample period.[19]

We use the transaction records to create quality-adjusted price indices which we then apply to our calculations of *unrealized* holding period returns in Section 5.1. We compare several candidate price indices, including official government indices and realty-based indices, but settle on our own index displayed in Figure 1 based on the matching estimator approach of McMillen (2012), since it reflects the near universe of sales (including short-term sales) and covers the longest time period in the pre-reform period. We discuss our indexing methods in Appendix C, but note that the candidate indices all closely track each other.

3.3 Summary Statistics: Before vs. After the Reform

In the top panel of Table 1, we present summary statistics for sales conducted within one year on either side of the reform, as well as for different windows of within less than one year of the reform. Overall sales volume declines by 44% within a year of the TTS, and holding period lengths nearly double. The tax was immediately salient to investors, who shifted their horizon beyond two years to avoid paying the surcharge. In unreported results, we find short-term sales volumes converged to a new steady state within six months, with bunching around the one-year notch stabilizing by the fourth month after the reform. This almost immediate convergence suggests a minor role for optimization frictions documented in other bunching contexts (e.g. Kleven & Waseem 2013; Gelber, Jones, & Sacks 2020).

The bottom panel of Table 1 shows how the composition of home sales changes across different parts of the *ex ante* sale value distribution around the TTS reform. Second home sales volume contracts by roughly one-third, and holding period length almost doubles regardless of property value. While growth is initially negative, unit prices return to their pre-reform level within a year. Unit prices exhibit mild growth of 2% for properties at the top pre-reform price distribution, but a 5% decline at the bottom of the distribution.

Price growth could be due to two channels: one is a selection effect whereby only relatively high quality properties with a holding period above two years get offloaded in the aftermath of the reform, leading to a mechanical increase in average prices paid. Another channel is sellers may now seek higher prices as compensation for the increased tax burden. Since sales volume collapses following the reform, investment-grade real estate may very well have become a "seller's market." We provide evidence of the latter channel using quality-adjusted

[19]We downloaded the rental survey data from TW Houses.

TABLE 1. Summary Statistics for Home Sales around the TTS Reform

	Sales volume			Holding period length				Unit prices				Unit price volatility		
	Before	After	Growth	Before	After	Growth	t-stat	Before	After	Growth	t-stat	Before	After	Growth
< 1 year	120,265	67,197	−44%	579	1,071	85%	171.12	80,178	80,601	0%	0.47	61,611	59,845	−3%
< 6 months	65,761	30,748	−53%	566	1,059	87%	122.29	80,234	80,152	−0%	-0.06	68,471	56,999	−17%
< 3 months	34,215	14,350	−58%	534	1,083	103%	96.74	80,669	77,837	−4%	-1.42	79,100	54,233	−31%
< 2 months	24,488	9,252	−62%	505	1,102	118%	87.71	84,191	77,962	−7%	-2.40	87,676	56,048	−36%
< 1 month	14,944	4,120	−72%	486	1,137	134%	68.68	81,910	71,435	−13%	-3.03	81,535	49,219	−40%
First quintile	2,264	1,483	−34%	624	1,171	88%	27.32	42,372	40,500	−5%	-2.25	25,048	24,807	−1%
Second quintile	2,339	1,395	−40%	607	1,097	81%	24.42	59,090	56,834	−4%	-1.98	34,594	33,102	−1%
Third quintile	2,250	1,493	−34%	576	1,075	87%	25.78	70,207	74,480	6%	3.10	36,208	44,381	23%
Fourth quintile	2,214	1,477	−33%	550	1,031	87%	25.03	93,960	92,918	−1%	-0.60	47,170	54,846	16%
Fifth quintile	2,279	1,447	−36%	538	1,045	94%	27.18	135,835	138,359	2%	0.92	91,314	74,498	−18%

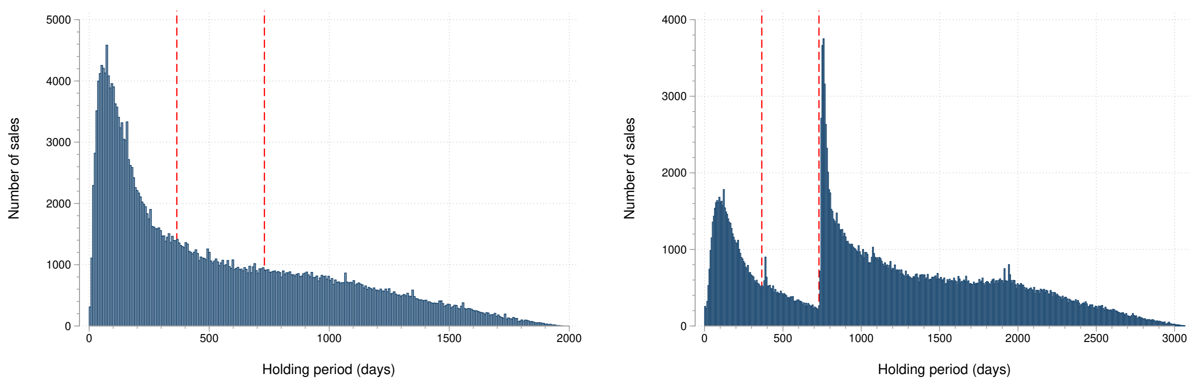
Notes: The top panel shows how overall sales volume, average holding period length, average unit prices (in NTD per square meter of floor space), and unit price volatility evolve by window length around the reform. For instance, <1 month subsets to home sales occurring either one month before or after the reform, whereas <1 year looks at a symmetric 365 day window around the reform. Unit price refers to the price per square meter of land, or in the case of an apartment unit, price per square meter of floor space. The bottom panel instead shows how the same variables change within a one-year window before vs. after the reform, split by quintiles of the last observed pre-reform real sale price for the property. We report the t-statistics of two-sample t-tests with unequal variances on the before vs. after differences.

prices in Appendix C and document positive pricing spillovers to sales in the owner-occupied segment of the market which was not directly taxed. This positive aggregate price growth after the flip tax, as displayed in Figure 1, is consistent with the liquidity crunch predicted by our theoretical model, wherein properties are in fixed supply and potential buyers substitute towards renting due to reduced home inventory.

Overall volatility in the second home market declined by 3% within a year of the reform, with volatility initially dropping by around 30% within the first few months of the reform before recovering to pre-reform trend within a year, as investors who waited to reach the two-year threshold began to sell. The 18% drop in unit price volatility for prime properties while volatility increased for more affordable properties suggests significant market segmentation. More generally, the summary statistics echo Umlauf (1993), Jones & Seguin (1997), and Hau (2006), who provide evidence that increasing transaction costs in securities markets increases price volatility, which goes against the logic of Tobin's (1978) proposal for a round-trip sales tax. Whether volatility increases or decreases for specific market segments is theoretically ambiguous and depends on the composition of buyer and sellers' beliefs about fundamental value. We formally show this within our model environment in Appendix A.1.

FIGURE 2. Distribution of Sales Volume by Holding Period

A. Pre-Reform Period B. Post-Reform Period



Notes: Each panel shows the distribution of second home property sales, restricting to properties with a clearly defined holding period. Panel A is the distribution for the three years prior to June 1, 2011, while Panel B is the distribution for the three years following the TTS reform. The vertical red dashed lines indicate the one-year and two-year holding period notches. We bin holding period lengths by week.

4 Quantity Responses to the Transfer Tax

In this section we present our main results on the effects of the TTS reform on sales volume, exploiting bunching around the holding period thresholds to identify the volume semi-elasticity as a sufficient statistic for the optimal tax rate formula given by (2.15).

4.1 Before vs. After Volume Comparisons

Figure 2 compares the distribution of sale frequency for second homes by holding period for three years before (Panel A) versus three years after (Panel B) the transfer tax was implemented. The figure illustrates three behavioral responses: first, there is clear evidence of bunching above the one-year and two-year holding period notches. The bunching response is much larger around the two-year notch where the transfer tax rate drops from 10% to 0%, implying that many investors simply delay sales by up to two years to avoid paying the tax.

Second, the TTS reform was very effective at reducing the number of sales with a holding period of less than one year. Prior to 2011, about two-thirds of all flips occurring within two years have a holding period of less than one year. Even though the surcharge rate drops from 15% to 10% across the one-year holding period notch, compared to the pre-reform distribution the implied excess mass for a six-month window around this notch is negative. Since newly constructed buildings are not subject to the transfer tax surcharge, the high volume of short-term flips in the *ex ante* period reflects the relative absence of other search frictions in the second home market. In Appendix B, we estimate the minimum amount of time required to close a residential property sale after identifying a buyer to be 38 days, with an average duration of 113 days for transactions in Taipei. Thus, the high number of sales occurring within a six-month holding period pre-2011 is plausible.

Third, the comparison between the pre-reform and post-reform distributions shows short-term unraveling in the investment property market. Sales to the right of the two-year holding period notch only account for the drop in sales to the left of the notch once we include all properties with holding periods up to 2,000 days. Hence, in many cases, investors may already hold a property long enough to incur no surcharge but are unable to quickly find a buyer, implying a deterioration in liquidity.

In Appendix D, we further quantify this liquidity crunch using listings data from a large, anonymous brokerage firm. Mean time on market (TOM) increases by 7 days after the TTS reform (p-value = 0.000). We show using difference-in-differences specifications that this is driven by the directly taxed non-owner occupied homes which experience a two-week increase in TOM relative to owner-occupied listings which are exempt. However, this is a small increase in search costs relative to the size of the tax, implying search frictions do not play a prominent role in our setting with speculative housing investors. Indeed, when we formally incorporate search costs into our heterogeneous investor model and calibrate to the listings data in Appendix A.2, we find the optimal flat tax rate decreases by only 0.22 p.p.

4.2 An Hedonic-Logit Counterfactual Model of Flips

A simple excess mass calculation based on comparing the pre-reform and post-reform distributions in Figure 2 may not be informative about the true extent of missing sales due to the tax. For instance, there may be macroeconomic trends unrelated to the tax which lead to changes in the composition of properties sold. A common approach to constructing counterfactuals in the literature is to fit local polynomial regressions to transactions data around the policy cutoff of interest (e.g. Chetty et al. 2011; Kleven & Waseem 2013; Best & Kleven 2018). In our setting such an approach can be summarized by the following regression:

$$q_j = \sum_{k=0}^{p} \beta_k \cdot (h_j)^k + \sum_{j=h_-}^{h_+} \gamma_k \cdot \mathbb{1}\{h_j = k\} + \nu_j \tag{4.1}$$

where q_j refers to the mass in holding period bin j and h refers to the length of the holding period within the bin. $[h_-, h_+]$ is an excluded range of holding period lengths around either the one-year or two-year threshold. The counterfactual bin counts are then obtained as the fitted values from the polynomial of order p via: $\widehat{q_j} = \sum_{k=0}^{p} \widehat{\beta}_k \cdot (h_j)^k$. We obtain nonsensical results when we use an excluded range to construct a counterfactual distribution of sales by holding period. Excluding properties around the one-year and two-year thresholds generates a counterfactual where sales volume for holding periods of six months or less is actually *higher* in the post-reform data than the predicted volume. If we took these results seriously, we would erroneously conclude that the transfer tax surcharge increased net trading volume.

The problem is, unlike transfer taxes which introduce price notches, the discontinuities in our setting are in terms of units of time. Since a homeowner's decision to sell a property today has a persistent influence on sales in future dates, there can be no well-defined concept of an excluded region when the tax regime introduces holding period notches. Doubly problematic is the fact that the transfer tax we study features two time discontinuities which are relatively close together, so any behavioral responses around the one-year threshold will likely have large effects on sales volume around the two-year threshold.

We address these concerns by estimating an hedonic-logit model on the pre-reform transaction data.[20] We then apply the fitted sale probabilities to construct what the distribution of sales would have looked like in the absence of the tax, conditional on available property amenities. The procedure can be described by the following equations:

$$f_{i,t} = \Pr\Big(y_{i,t} = 1 | \mathbf{X_{i,t}}, \delta_t, \beta\Big) = \frac{1}{1 + \exp(-\delta_t - \beta' \cdot \mathbf{X_{i,t}})} \tag{4.2}$$

$$y_{i,t} = \mathbb{1}\{\delta_t + \beta' \cdot \mathbf{X_{i,t}} + \epsilon_{i,t} > 0\} \tag{4.3}$$

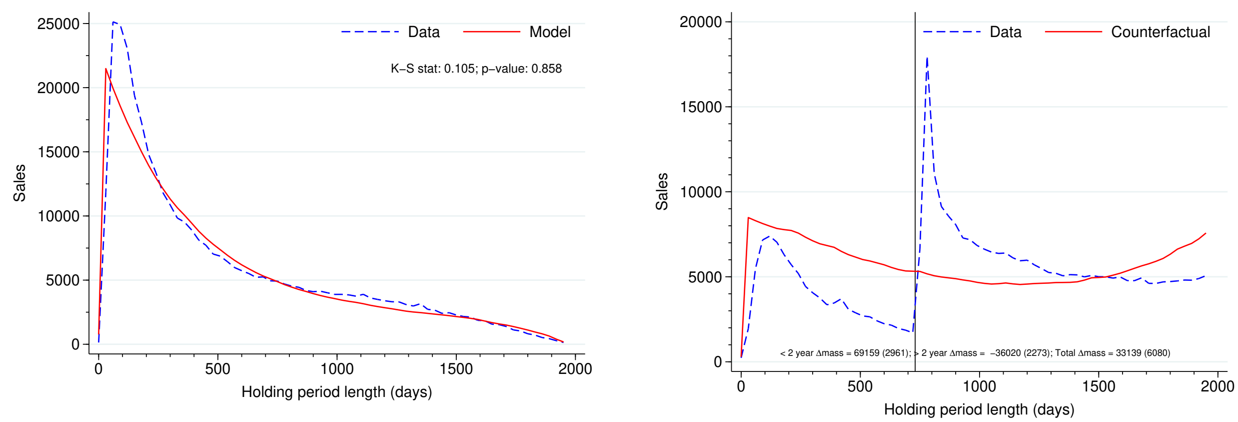
$$\widehat{q}_j = \sum_{i=1}^{N_j} \widehat{f}\Big(\mathbf{X_{i,t}};\ \widehat{\delta}_\mathbf{t}, \widehat{\beta}\Big) \tag{4.4}$$

The first two equations specify a logit model of sale probability where we include month-year, day-of-week, and week-of-month fixed effects, as well as a holiday dummy in the vector of time fixed effects δ_t. A set of potentially time-varying property characteristics $\mathbf{X_{i,t}}$ adjusts for compositional changes in the market, and includes a polynomial of holding period length. The last line computes the counterfactual sales volume in holding period bin j by integrating up from the fitted probabilities $\widehat{f_{i,t}}$ for each property i in the *post-reform* period. Collier, Ellis, & Keys (2021) apply a similar covariate-adjustment procedure in their analysis of thresholds above which posting housing as collateral is required in consumer credit markets. Computing excess mass in this way also helps account for house and investor characteristics which might be correlated with the endogenous running variable (i.e. holding period length).

[20]We obtain similar missing sales numbers if we instead estimate a linear probability model (LPM) or probit. Conditional on the same RHS set of covariates, we find the tax generated missing sales volume equal to roughly half of average annual sales in the pre-reform period. The LPM generates fitted values greater than one, leading to overestimates of missing sales.

FIGURE 3. Covariate-Adjusted Sales Volume by Holding Period Length

A. Model Fit to Pre-Reform Data B. Post-Reform Counterfactual and Data



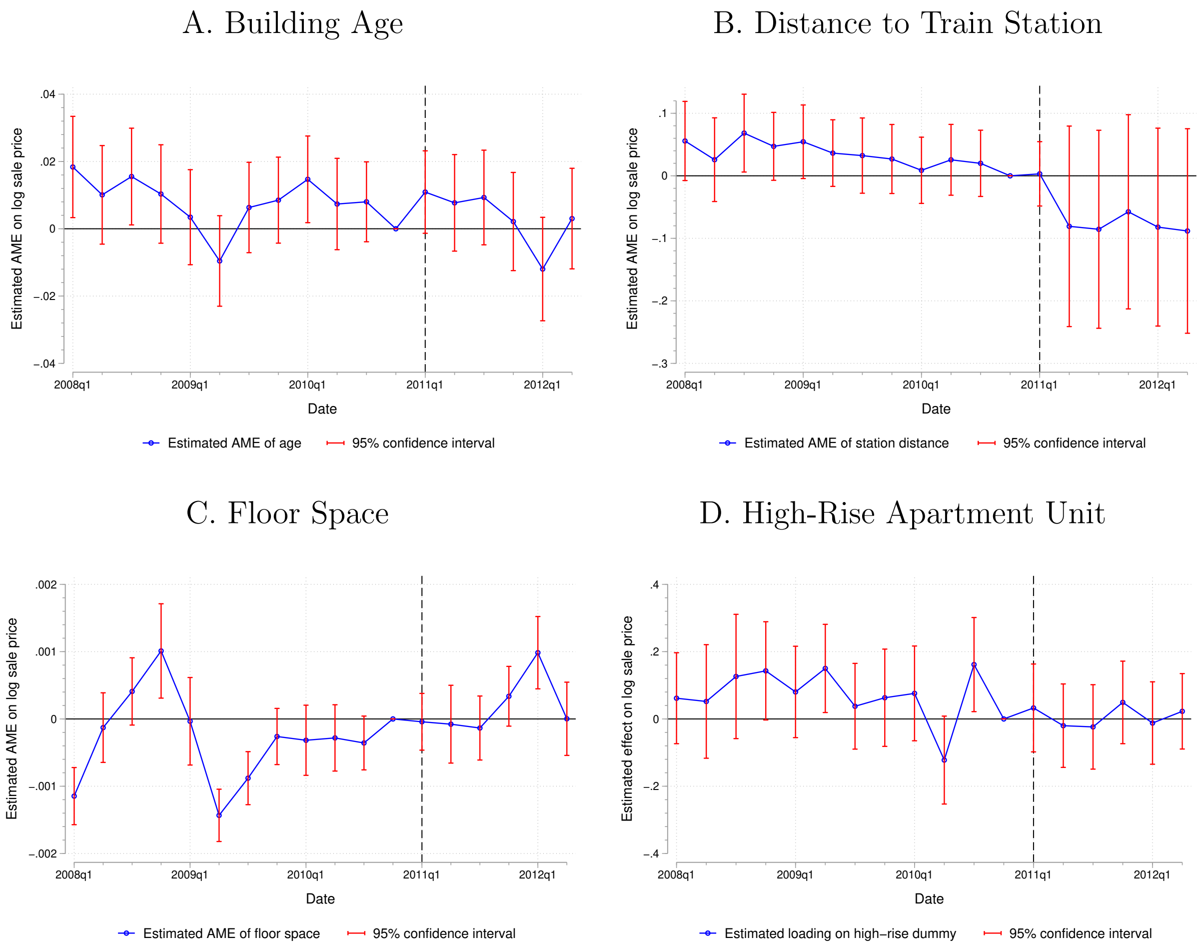
Notes: The figure plots the distribution of sales volume by holding period length estimated via (4.2)–(4.4) against the empirical distribution. Panel A does this for the pre-reform data and model fit to the pre-reform data. Panel B does this for the post-reform data and the model trained on the pre-reform data but fit to the post-reform period, which forms our counterfactual. The full logit model includes month-year, week-of-month, day-of-week fixed effects, a holiday dummy, a quadratic in property age (based on the construction date), dummies for structure material, dummies for use category (apartment vs. single-family home), floor space, land area, holding period length, number of floors and building floor dummies, and distance to the nearest commuter train station. We bin holding period lengths by month. In Panel A, we report the p-value for the Kolmogorov-Smirnov test of the null of equivalence between the data and model-implied distributions. We obtain standard errors on the missing sales mass using the bootstrap procedure of Chetty et al. (2011).

The identifying assumption for $\widehat{q}_j$ to be an appropriate counterfactual for sales volume is that, in the absence of the TTS, the market would have priced property amenities in $\mathbf{X_{i,t}}$ in the same way as in the pre-reform period. We assess the validity of this assumption in two ways. First, we check how well the model fits the empirical distribution in the pre-reform period. Panel A of Figure 3 shows that our model fits the empirical distribution quite well. We obtain a p-value of 0.86 for the Kolmogorov-Smirnov test of the null of no difference between the empirical and model-implied sales distributions.[21] Second, we run versions of the model in (4.2)–(4.3) where we interact property characteristics such as age with quarter-year fixed effects and check for pre-trends in the estimated factor loadings. The absence of pre-trends in the average marginal effects plotted in Figure 4 suggests that the transfer tax did not alter demand for property amenities included in our hedonic model.

Panel B of Figure 3 illustrates that the TTS reform crowded out about 33,000 sales, or 40% of a year's worth of pre-reform sales volume, and generated a roughly 75% drop in one-year flips. This translates to a volume semi-elasticity in the optimal tax formula (2.15)

[21]We discuss how our failure to fully predict *ex ante* short-term sales volume influences our optimal flat tax results in Section 6.1.

FIGURE 4. Pre-Trend Tests: Average Marginal Effects on Housing Prices



Notes: Each panel plots the time-varying average marginal effects (AMEs) of property characteristics from a pricing regression of the form described in Appendix C. For the continuous variables (building age, distance, floor space), we plot marginal effects from a quadratic specification ($\beta_{t,1} + 2\beta_{t,2}$). The transfer tax surcharge on second home flips was announced at the beginning of 2011Q1. We normalize all coefficients relative to the last quarter before the announcement (2010Q4). All regressions include separate time fixed effects. We exclude newly built properties with age < 1 year. We define train station distance as the minimum among the distances to a metro stop, commuter rail, or high speed rail station. High-rise apartment units are those above the 10th floor (top decile). We winsorize prices and continuous covariates at the 1st/99th percentiles. Red bars indicate 95% confidence intervals with standard errors clustered by property block.

of $-75/15$ p.p. $= -5$. We show robustness of our missing sales estimates to different logit specifications later in the optimal flat tax calibrations of Table 7 in Section 6.1. Interestingly, the estimated counterfactual curve suggests the tax not only discouraged sales to the left of the two-year threshold, but also at holding periods beyond four years in length. Hence, a seller may have trouble finding a buyer in the market for investment properties even if that seller does not face the tax liability themselves.

Which types of investors are most discouraged by the flip tax? We tabulate missing sales by sellers' estimated quintile of net worth as of 2010 by applying the same model in (4.2)–(4.4) to obtain fitted values for properties sold to taxpayers within each net worth quintile. 44% of the overall missing mass originates from sellers in the bottom fifth of the wealth distribution. The proportion is also approximately the same when we examine crowd out of the fraction of sales within a two-year holding period. In light of this evidence that low-wealth individuals are an important source of speculative activity, we analyze in Section 5.1 whether the speculators that were crowded out in the low end of the wealth distribution were misinformed, but find that they earned *higher* tax-adjusted holding period returns.

Similarly, when we separately apply the same counterfactual model to local and out-of-town (OOT) sellers, we calculate a missing mass of sales for the segment of the market involving OOT sellers that is 2.4 times greater than the missing mass due to local sellers, and 1.2 times greater than the missing mass estimated over the entire, pooled sample of transactions. Non-local investors thus respond more to the tax along the quantity dimension. In the next section, we ask whether these non-local investors are noise traders – à la the model in Section 2 – but ultimately find that locals and non-locals earn statistically similar net-of-tax holding period returns, conditional on other investor and property characteristics.

5 Identifying Noise Traders in Housing Markets

In this section we identify the second sufficient statistic we require to back out the optimal transfer tax rate via equation (2.15): the *ex ante* share of non-fundamental trading.

5.1 Tags for Noise Trading and Returns to Flipping

We start with an examination of how other frequently referenced tags for noise trading relate to holding period returns. A commonly recounted narrative of the 2000s U.S. boom is that many cities which experienced a pricing boom in the absence of clear restrictions on new real estate supply saw an influx of capital from non-local, or "out-of-town" (OOT) investors. Second home investors in that episode were more likely to be low-income or low-wealth individuals buying bottom tier properties, were heavily mortgaged, and earned lower capital gains (Haughwout et al. 2011; Chinco & Mayer 2016; García 2019).

The richness of our transactions records linked to personal income tax returns and wealth statements allows us to look beyond capital gains – we can analyze the role of taxes, mortgage interest payments, and rental income in generating heterogeneous returns. OOT investors may lack knowledge about local conditions which prevents them from timing the market as proficiently as residents, yet they may have more flexibility with regards to location, and therefore may garner higher returns due to tax arbitrage. We test for this possibility using the following definition of (net) total holding period returns at the taxpayer level:

$$r_{t-1,t}^{i} = \frac{\sum_{j=1}^{n}(1-\tau_{j,t})\cdot\widetilde{V}_{j,t}^{i}+(1-c_{j,t}^{i})\cdot Y_{j,t}^{i}-T_{t-1,t}^{i}}{\sum_{j=1}^{n}\widetilde{V}_{j,t-1}} - 1 \tag{5.1}$$

where r_t^i is the holding period return for the set of properties held by taxpayer i between $t-1$ and t. $\tau_{j,t}$ is the fraction of the market value $\widetilde{V}$ the seller pays in transfer taxes on property j, $c_{j,t}^i$ is the income tax paid by i on rental income $Y_{j,t}^i$ accumulated between $t-1$ and t, and $T_{t-1,t}^i$ refers to the total property tax bill incurred by i during the holding period.

If a property j does not transact in period t, we inflate up from the previous transaction price in $t-1$ using our estimated price index $\widehat{P}$ from Appendix C, and assuming a linear rate of depreciation that we estimate to be 2%, following the methods of LaPoint (2021):

$$\widetilde{V}_{j,t} = (1-\delta)\cdot V_{j,t-1} \times \frac{\widehat{P_{j,t}}}{\widehat{P_{j,t-1}}} \tag{5.2}$$

We annualize returns by computing $(1+r_{t-1,t}^i)^{365/n}$, with n days in the holding period.[22] In Appendix A.3, we combine (5.1) and (5.2) to perform an alternative calibration of the optimal tax model which sets the flat tax rate equal to the gap between buyer and seller expected returns. Calibrating to expected returns generates a nearly identical tax rate to the one we obtain when we use our preferred noise trading measure introduced in Section 5.2.

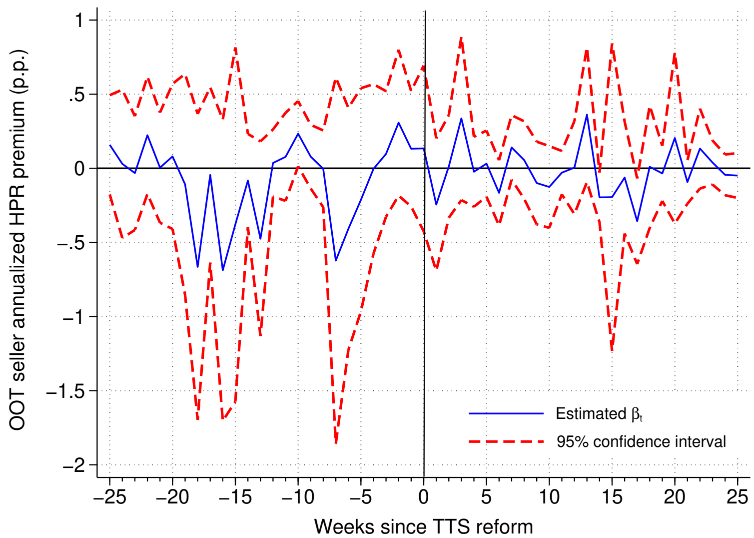
We conduct two tests for whether local sellers earn a premium relative to out-of-town sellers (or vice versa). To start, we exploit the fact that taxpayers file returns each year to estimate the following repeat investor event study specification which examines how realized capital gains evolve around the transfer tax reform:

$$r_{i,j,t} = \sum_{t=-T}^{T}\beta_t \cdot OOT\_seller_{i,j,t} + \eta_i + \delta_t + \gamma' \cdot \mathbf{X_{j,t}} + \epsilon_{i,j,t} \tag{5.3}$$

where $r_{i,j,t}$ is the annualized capital gain investor i has earned on property j as of date t, η_i is the investor fixed effect, δ_t is a full set of time dummies for day-of-week, 7-day, and public holidays, and $\mathbf{X_{j,t}}$ is a set of controls for potentially time-varying property characteristics. OOT_seller is a dummy equal to unity if i resides in an administrative region different from where property j is located. We plot the estimated coefficients $\widehat{\beta}_t$ which capture the (weekly)

[22] Our results in this section are robust to using either our matching estimator indexing method of Appendix C or a translog hedonic method à la LaPoint (2021) to inflation-adjust holding period returns and estimate δ. We assume a translog housing production function to recover depreciation rates, as this allows us to leverage the full set of transactions rather than only using repeat sales.

FIGURE 5. Repeat Investor Event Study of OOT Return Premia



Notes: The figure plots the estimated event study coefficients $\widehat{\beta}_t$ obtained from the regression in (5.3) for annualized capital gains measured at the property level. The regression includes a full set of time dummies and taxpayer id fixed effects, as well as controls for the quality of the property. 95% confidence intervals in red dashed lines obtained from clustering standard errors at the taxpayer id level.

OOT premium in Figure 5. The estimated OOT premium hovers around zero, and there is no clear change in the premium after enactment of the transfer tax reform. Local investors do not appear to be any better or worse at timing the market with their housing flips.

For our second test of local seller premia, we estimate pooled OLS versions of (5.3) where we use the total net-of-tax holding period return definition in (5.1) as the outcome and decompose the OOT premia depending on whether the buyer is local. The results of this exercise, reported in Table 2, mirror those in Figure 5. Once we control for investor fixed effects we do not find any evidence in favor of OOT premia in total holding period returns resulting from the flip tax, regardless of the residency status of the buyer. Although there is a statistically significant negative premium earned by OOT investors in columns (1) and (5) where we do not include taxpayer fixed effects, this amounts to a mere 3 basis points.[23] Hence, OOT investors do not earn a premium through tax arbitrage or geographic diversification.

We document four stylized facts about housing returns which undermine the validity of several other proxies for noise trading invoked in the literature. Each of the following results survives the inclusion of taxpayer fixed effects. (i) Annualized holding period returns decline linearly with investors' net worth. For instance, sellers in the first quintile of taxpayer net worth earn average annualized returns of 28.0%, compared to 18.3% among sellers in the

[23] A triple differences in means estimate corresponding to the regression in Table 2 column (5) but without controls results in a 4 basis point premium with a p-value of 0.98.

TABLE 2. Difference-in-Differences Analysis of OOT vs. Local Counterparty Returns

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
OOT_seller $\times$ *Post*	-0.03^{***}	-0.02^{*}	-0.02	-0.04				
	(0.01)	(0.01)	(0.02)	(0.05)				
OOT_seller $\times$ *OOT_buyer* $\times$ *Post*					-0.03^{***}	-0.02	-0.02	-0.03
					(0.01)	(0.02)	(0.02)	(0.05)
OOT_seller $\times$ *Local_buyer* $\times$ *Post*					-0.03^{**}	-0.02	-0.01	-0.02
					(0.01)	(0.01)	(0.02)	(0.07)
Local_seller $\times$ *OOT_buyer* $\times$ *Post*					0.01	0.00	0.01	0.06
					(0.01)	(0.01)	(0.02)	(0.08)
City $\times$ year FEs	✓	✓	✓	✓	✓	✓	✓	✓
# of houses	✓		✓		✓		✓	
Wealth quintile dummies	✓		✓		✓		✓	
Taxpayer id FEs		✓		✓		✓		✓
Property id FEs			✓	✓				✓
N	76,337	38,194	26,370	6,551	76,337	38,194	26,370	6,551
Adj. R^2	0.02	0.44	0.43	0.44	0.02	0.44	0.43	0.44

Notes: The table displays results from estimating pooled OLS versions of equation (5.3), where the outcome variable is the total holding period return computed via (5.1). All coefficient values are in percentage points. # of houses refers to dummies for the number of houses in the seller's portfolio as of the last pre-reform tax filing year (2010), and wealth quintile pertains to dummies for the seller's net worth quintile in 2010. In columns (5) through (8), we include additional sets of dummies interacted with the post-reform dummy to distinguish between counterparty pairs where either the buyer or seller (or both) are non-local to the transaction, and the omitted case consists of transactions where both the buyer and seller have a permanent address in the administrative region where the property is located. Standard errors in parentheses clustered by taxpayer id, which determines out-of-town status. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

top quintile (p-value on difference in means < 0.001). (ii) Sellers of mortgaged properties – observed from deductions for interest payments against personal income taxes – earn statistically similar capital gains to unleveraged sellers. (iii) Stock market participants earn lower returns than investors holding no equities (12.7% vs. 24.8% annualized, on average). (iv) Both before and after the transfer tax hike, the term structure of holding period returns is downward sloping within the first 12 months, and roughly flat for longer holds.[24]

To summarize, our bunching analysis generally agrees with the quantity patterns witnessed in other real estate markets – namely, that OOT and low wealth investors account for the majority of property flips crowded out by transfer taxes. However, our tax and income-adjusted returns show that speculators, proxied by a variety of standard empirical tags, *do not* appear to be misinformed. This accords with Bayer et al. (2020), who argue

[24]Chambers, Spaenjers, & Steiner (2021) compute property-level returns for a set of Oxford-Cambridge colleges over a 70-year period. Like Giglio et al. (2021), conclude that long-term gross income yields for residential properties trend towards zero. Sagi (2021) documents a downward-sloping term structure for realized gross returns to commercial real estate, and Giacoletti (2021) does the same for housing.

that investors function as intermediaries and may improve house price efficiency. Therefore, to calibrate the optimal flat flip tax rate from Section 2.1, we propose an alternative method for isolating the fraction of non-fundamental, or noisy, property sales volume.

5.2 Severe Weather Shocks & Speculative Flips

Our strategy for identifying the share of non-fundamental trading in the numerator of the optimal tax formula in (2.15) is inspired by a growing literature documenting the influence of weather on economic activity.[25] The basic notion is that selling a home generates fixed costs. Individuals who wish to sell a home for fundamentals-based reasons have a higher threshold fixed cost beyond which they will not sell, and thus a smaller inaction region in pricing interval length, compared to owners with biased beliefs. A persistent, positive shock to fixed costs of selling will then disproportionately force out noise traders. In Appendix A, we add housing search costs to our baseline framework to formalize the link between non-fundamental trading volume and weather conditions.

We use variation in the severity of typhoon seasons in Taiwan during the period (2006Q2-2011Q2) before the transfer tax surcharge to identify shocks to the fixed cost of selling a home. We collect daily data from all meteorological stations managed by the Taiwan Central Weather Bureau. These stations record weather conditions which are used to forecast and classify tropical storms, including wind speed, precipitation, humidity, low sea pressure, and temperature. We describe the weather station data and provide scientific context for Pacific storm seasons in Appendix E.

We start by estimating time series regressions of the following form:

$$Volume_t = \beta \cdot (Weather_t \times Summer_t) + \delta_t + \gamma' \cdot \mathbf{X_t} + \varepsilon_t \tag{5.4}$$

where $Volume_t$ is total transactions on date t. $Weather_t$ is a meteorological reading, averaged across the main weather stations which are staffed by a person. The typical typhoon season runs from July to September, with 80% of all official typhoon forecast warnings occurring during those months, so we set the dummy $Summer_t$ equal to unity during July, August, or September. The interaction of $Weather_t \times Summer_t$ captures how the effects of weather variables on the real estate market are amplified in the summer months due to the confluence of extreme conditions (e.g. wind gusts + torrential rain + high temperatures and humidity).

[25]Papers in this literature include Goetzmann et al. (2014), who show that cloudy days induce pessimistic sentiments in equities markets. Dell, Jones, & Olken (2014) summarize the methods researchers use in economics to identify treatment effects from weather shocks. Goetzmann & Zhu (2005) show NYSE spreads widen on cloudy days, implying weather conditions generate market frictions.

TABLE 3. Severe Weather Shocks and Real Estate Sales

	(1)	(2)	(3)	(4)	(5)	(6)
Max WS × *Summer*	-2.27^{**}		-1.16			
	(0.95)		(0.98)			
Rainfall × *Summer*		-0.32^{***}	-0.26^{***}	-0.31^{***}		-0.24^{**}
		(0.10)	(0.10)	(0.10)		(0.10)
$\mathbb{1}\{T > 32°C\}$				5.14		
				(6.88)		
$\mathbb{1}\{27 < T \leq 32°C\}$				1.51		
				(4.03)		
$\mathbb{1}\{\text{Max WS} \geq 74\text{mph}\}$					-65.98^{***}	-27.49^{**}
					(15.52)	(13.32)
$\mathbb{1}\{55 \leq \text{Max WS} < 74\text{mph}\}$					-10.88	-9.18
					(9.85)	(7.47)
7-day FEs	✓	✓	✓	✓	✓	✓
Day-of-week FEs	✓	✓	✓	✓	✓	✓
Damages controls	✓	✓	✓	✓	✓	✓
N	1,973	1,973	1,973	1,973	1,973	1,973

Notes: The table presents results from estimating (5.4). The outcome variable in each column is 100 times the deviation of aggregate log sales volume from its 6-month symmetric moving average. RHS variables include maximum wind speed and accumulated rainfall interacted with a dummy for the summer typhoon season, dummies for daily high temperature ranges, a dummy for gusts over 74 mph (typhoon), and a dummy for gusts between 55-73 mph (tropical storm). We include daily observations from the pre-reform period during which our sales and weather datasets overlap: January 1, 2006 through May 31, 2011. All regressions control for daily counts of casualties and properties severely damaged due to flooding and typhoons (see Appendix E for details). Newey-West standard errors with six lags in parentheses adjust for serial correlation and heteroskedasticity. We select the minimum possible lag order such that the estimator for the covariance matrix is consistent (Newey & West 1987). $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

We control for counts of property damage incidents in $\mathbf{X_t}$ to rule out drops in volume due to weather-induced changes in the underlying quality of the housing stock. δ_t includes a full set of day-of-week, 7-day fixed effects, and holiday dummies to strip out seasonality.

Our results from estimating equation (5.4) in Table 3 show a robust negative effect of accumulated daily rainfall on volume, but no effect of maximum wind gusts conditional on rainfall.[26] Severe rainfall increases the costs to commuting, restricts outside activity, and may even result in flooding. Even after controlling for temperature (column 4) or for high wind speeds that trigger official typhoon and tropical storms (column 6), rainfall continues to exert a stable and statistically significant effect on sales volume.[27] A one millimeter increase in accumulated daily rainfall lowers volume by about 0.3% relative to its six-month moving

[26]In Appendix E, we provide further support for our focus on rain and wind as proxies for weather shocks by conducting factor analysis using a richer set of atmospheric conditions.

[27]While high wind speeds also hinder the process involved in listing a house, given the historical prevalence of typhoons in the southern Pacific, power grids and building materials are designed to limit damages. The majority (81%) of property sales in our sample involve units in reinforced concrete buildings.

TABLE 4. Testing for Pent-up Sales after Storm Season

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Rain_t \times Summer_t$	-0.33^{***}	-0.33^{***}	-0.32^{***}	-0.32^{***}	-0.33^{***}	-0.33^{***}	-0.32^{***}	-0.31^{***}
	(0.08)	(0.09)	(0.10)	(0.10)	(0.10)	(0.09)	(0.09)	(0.10)
$\overline{Rain}_{t-1w,t-1} \times Summer_t$	-0.57							
	(0.52)							
$\overline{Rain}_{t-2w,t-1} \times Summer_t$		-0.30						
		(0.37)						
$\overline{Rain}_{t-4w,t-1} \times Summer_t$			0.47					
			(0.76)					
$\overline{Rain}_{t-8w,t-1} \times Summer_t$				0.83				
				(1.36)				
$\mathbb{1}_{t-1w,t-1}\{\overline{Rain} \geq 0.5\text{in.}\}$					-10.33^{*}			
					(6.08)			
$\mathbb{1}_{t-2w,t-1}\{\overline{Rain} \geq 0.5\text{in.}\}$						-7.34		
						(8.42)		
$\mathbb{1}_{t-4w,t-1}\{\overline{Rain} \geq 0.5\text{in.}\}$							-3.03	
							(8.32)	
$\mathbb{1}_{t-8w,t-1}\{\overline{Rain} \geq 0.5\text{in.}\}$								18.85
								(13.46)
7-day FEs	✓	✓	✓	✓	✓	✓	✓	✓
Day-of-week FEs	✓	✓	✓	✓	✓	✓	✓	✓
Damages controls	✓	✓	✓	✓	✓	✓	✓	✓
N	1,973	1,973	1,973	1,973	1,973	1,973	1,973	1,973

Notes: The table presents results from estimating (5.5). The outcome variable in each column is 100 times the deviation of aggregate log sales volume from its 6-month symmetric moving average. The RHS variables are either the moving average of daily accumulated rainfall, or indicators for whether the moving average of daily accumulated rainfall exceeds 0.5 inches over a specific, lagged time horizon (one, two, four, or eight week periods). We include daily observations from the pre-reform period during which our sales and weather datasets overlap: January 1, 2006 through May 31, 2011. All regressions control for daily counts of casualties and properties lost due to flooding and typhoons (see Appendix E for details). Newey-West standard errors with six lags in parentheses adjust for serial correlation and heteroskedasticity. We select the minimum possible lag order such that the estimator for the covariance matrix is consistent (Newey & West 1987). $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

average. A shock to rainfall of 74 mm (2.9 inches) produces the average precipitation observed during typhoons, resulting in a 20% drop in sales volume.

One concern is that our estimates of $\widehat{\beta}$ in equation (5.4) may not capture a drop in volume from noise trader exits if sellers simply delay sales by a few weeks to avoid weather shocks. That is, after a severe storm there may be pent-up demand for properties, indicating that a large fraction of the original drop in volume was due to short-run intertemporal substitution. We test for the possibility of pent-up demand using the following time series specification:

$$Volume_t = \beta_1 \cdot (Rain_t \times Summer_t) + \beta_2 \cdot (\overline{Rain}_{t-L,t-1} \times Summer_t) + \delta_t + \gamma' \cdot \mathbf{X_t} + \varepsilon_t \quad (5.5)$$

where, informed by our results in Table 3, we focus on severe rain as a positive shock to costs associated with selling properties.[28] The variable $\overline{Rain}_{t-L,t-1}$ refers to the average accumulated daily rainfall over the previous L days. Therefore, the "true" upper-bound drop in volume due to noise trader exits is given by $\widehat{\beta}_1 + \widehat{\beta}_2$.

The point estimates in Table 4 confirm that sales volume does not bounce back after a severe typhoon season ends. We identify a 0.3% drop in sales per one millimeter of rainfall regardless of whether we account for pent-up demand effects at a one, two, four, or eight-week horizon. We also check whether pent-up demand is a consequence of only particularly severe weather shocks by substituting $\overline{Rain}_{t-L,t-1}$ for dummies $\mathbb{1}_{t-L,t-1}\{\overline{Rain} \geq 0.5\text{in.}\}$, which are equal to unity when the average accumulated daily rainfall over the previous L days exceeds one-half inches.[29] While the coefficients on $\mathbb{1}_{t-L,t-1}\{\overline{Rain} \geq 0.5\text{in.}\}$ are never significant across our specifications, the point estimates remain negative up to four weeks after the initial shock, suggesting severe rainfall over a period of several weeks has a persistently negative effect on speculative volume. Overall, these results support our interpretation of the estimates in Table 3 as upper-bound measures of the noise trading share.

The daily event study analysis in Figure 6 shows that the persistent drop in sales volume around storms is not due to noise traders intertemporally shifting transactions forward in response to weather forecasts. Sales volume is flat in the week leading up to tropical-storm level rainfall (green) or typhoon-force winds (red). Moreover, investors only react to *realized* weather events and not to official storm warnings (blue), which are issued up to one week in advance of a storm making landfall. Consistent with the tests of pent-up demand in Table 5, volumes do not immediately bounce back after $t = 0$.[30]

In Table 5, instead of using overall sales volume as the outcome, we exploit spatial variation in exposure of local real estate markets to typhoon-like conditions by estimating a version of (5.4) at the district level. The geographic cross-sectional results difference out common macroeconomic trends in sales volume such as those due to mandated economy-wide shutdowns or government safety measures.[31] Still, we find areas with greater rainfall on a given date experience a larger decline in sales volume, and as in Table 3, wind speed has no consistent effect. Sales volume is 0.037% lower in a district experiencing a rainy day with 1 mm more of precipitation, even after controlling for average wind gust speed (column 4).

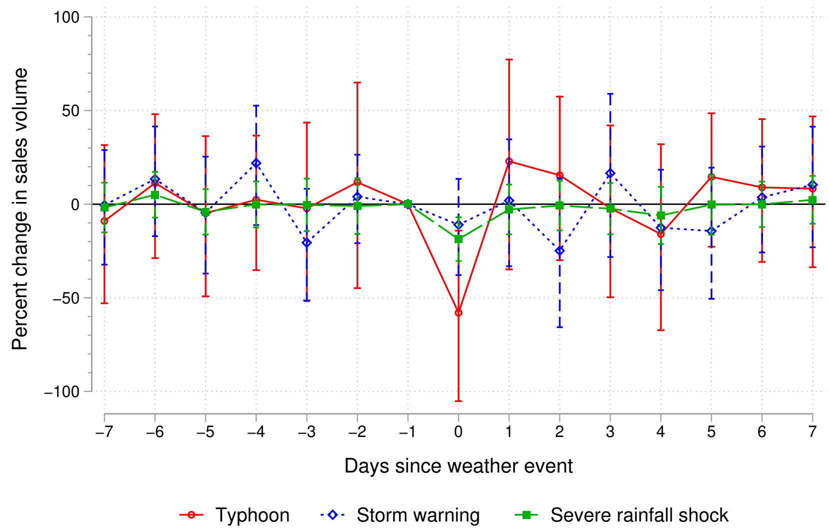
[28]The estimated $\widehat{\beta}_1$ remain unchanged when we include wind speed readings on the RHS of (5.5).

[29]Rainfall of a half inch or more is above the 80th percentile of daily rainfall, and 40% of such days coincide with official typhoon warnings for the entire island.

[30]Buyer-seller matching models in which buyers' purchase offers arrive in a Poisson fashion and weather shocks are a negative shock to the arrival rate can also generate this discrete and unrecovered drop in volume.

[31]In unreported results, we run a linear probability model at the property-level and find that typhoon events result in a 0.002% lower probability that a second home sells. See Appendix E for details.

FIGURE 6. Event Study Analysis of Sales Volume around Stormy Days



Notes: The figure plots the estimated $\widehat{\beta}_t$ from regressions of the form: $Volume_t = \sum_{t=-7}^{+7} \beta_t \cdot Weather_t + \delta_t + \gamma' \mathbf{X_t} + \varepsilon_t$. $Weather_t$ is a dummy equal to unity if date t features a confirmed typhoon event (red), or an official typhoon warning (blue), or rainfall consistent with the average tropical storm event (green). In each regression we include a full set of day-of-week fixed effects, 7-day fixed effects, holiday dummies, and controls for property damages, as in equation (5.4). We normalize the coefficients so that $\beta_{-1} = 0$. Bars indicate 95% confidence intervals obtained from Newey-West standard errors with six lags in parentheses adjust for serial correlation and heteroskedasticity. See Appendix E for details on the weather variable construction.

Finally, as a sanity check on our use of weather shocks to separate out noisy from non-noisy traders, we compare the proportion of sales associated with other tags for noise trading on dates with severe vs. normal weather. Table 6 confirms that severe rainfall crowds out flippers who would have been impacted by the transfer tax had it been in place. During days with tropical storm levels of rainfall (a roughly 2 s.d. shock), the share of transactions with a holding period of less than one year falls by 19 p.p. Rain shocks do not deter sales involving OOT counterparties, and they have only a small negative effect on sales by individuals who are trading properties in the absence of recent employment or marital status changes. Conditioning on all three tags results in a 15 p.p. reduction in noisy volume. Severe weather thus appears to replicate the quantity effects of a flip tax, but during the pre-reform period, providing an upper bound measure of the *ex ante* share of noise trading.

6 Tax Regime Calibration & General Policy Implications

What do the behavioral responses we have documented imply about the performance of property transfer taxes as a tool to improve pricing efficiency? In this section, we combine sufficient statistics identified from the Taiwan reform to produce an upper-bound optimal

TABLE 5. District-Level Results: Weather Shocks and Real Estate Sales

	(1)	(2)	(3)	(4)	(5)	(6)
Rainfall × *Summer*	-0.037^{**}	-0.038^{**}			-0.030^{**}	-0.037^{***}
	(0.015)	(0.015)			(0.015)	(0.014)
Max WS × *Summer*			0.043		0.116	
			(0.140)		(0.142)	
Avg. WS × *Summer*				−0.138		−0.012
				(0.383)		(0.382)
7-day FEs	✓	✓	✓	✓	✓	✓
Day-of-week FEs	✓	✓	✓	✓	✓	✓
District FEs	✓	✓	✓	✓	✓	✓
Damages controls		✓	✓	✓	✓	✓
N	101,141	101,141	88,078	98,666	88,076	98,627

Notes: The table presents results from estimating district-level panel regressions of the form: $Volume_{j,t} = \beta \cdot (Weather_{j,t} \times Summer_t) + \delta_t + \psi_j + \gamma' \cdot \mathbf{X_t} + \varepsilon_{j,t}$. The outcome variable in each column is 100 times the deviation of log sales volume in district j from its 6-month symmetric moving average. We include daily observations from the pre-reform period (Panel A) during which our sales and weather datasets overlap: January 1, 2006 through May 31, 2011. All regressions except the first column control for daily counts of casualties and properties lost due to flooding and typhoons (see Appendix E for details). Conley standard errors in parentheses adjust for spatial autocorrelation according to the distance between the centroid coordinates of each district. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

flat tax rate estimate of 4%. We then compute optimal tax rates for different groups of investors and probe how Tobin taxes redistribute wealth between renters and homeowners.

6.1 Calibration of Baseline Sufficient Statistics Formula

We have now identified the two parameters needed to estimate the optimal flat transfer tax given by equation (2.15): the semi-elasticity of volume with respect to the tax and the *ex ante* share of non-fundamental trading. Given our estimates of a roughly 75% drop in one-year flips from the bunching analysis, and a 20% non-fundamental trading share based on the results in Section 5.2, we obtain a semi-elasticity of $\epsilon = -75\%/15$ p.p. $= -5$, and an optimal flat tax rate of $\tau^* = 20\%/5 = 4\%$, compared to the actual tax rate of 15% on one-year flips.

It is less straightforward to map our estimate of the 40% overall drop in second home sales volume into a semi-elasticity due to the two holding period thresholds imposed by the policy. The fact that rates in this context discontinuously change along a time dimension means that market unraveling beyond the two-year threshold cannot be decoupled from the magnitude of the rate changes for short-term sales. An alternative, but conservative, estimate of an overall semi-elasticity would be $-40\%/10$ p.p. $= -4$, which supposes the drop from a 10% to 0% rate is the most important source of unraveling for longer holding periods. This assumption

TABLE 6. Rain Shocks and Possible Noise Trading Share Proxies

	OOT counterparty	No filing change	1-year flip	All
Overall	0.91	0.79	0.42	0.33
$<$ 1 s.d. rain	0.91	0.79	0.42	0.33
$\geq$ 1 s.d. rain	0.95	0.78	0.38	0.30
Difference	0.04^{***}	-0.01	-0.04^{***}	-0.03^{***}
	(13.87)	(-1.28)	(-7.30)	(-4.88)
$<$ 2 s.d. rain	0.91	0.79	0.42	0.33
$\geq$ 2 s.d. rain	0.99	0.76	0.23	0.18
Difference	0.08^{***}	-0.03^{**}	-0.19^{***}	-0.15^{***}
	(7.63)	(-2.20)	(-9.99)	(-8.58)

Note: The table displays the fraction of sales satisfying possible tags for noise trading during the pre-reform period. OOT counterparty refers to transactions where the buyer or seller (or both) has a permanent address in an administrative region other than where the property is located. No filing change refers to a sale where the seller is not selling their property within a year of changing their primary employer or tax filing status (i.e. married vs. single). 1-year flip refers to a transaction where the seller's holding period was less than or equal to 365 days in length. All refers to sales satisfying all of the three aforementioned conditions. 1 s.d. above average rainfall = 12 mm (0.47 in); 2 s.d. above average rainfall = 15 mm (0.59 in). A 2 s.d. rain shock corresponds to average rainfall during a tropical storm event. For each criterion, we compute the difference in sales shares on rainy and non-rainy days and conduct a two-sided t-test on the difference, with t-statistics in parentheses and $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

is consistent with the large bunching response at the two-year notch that is absent around the one-year notch. Such reasoning yields an optimal transfer tax of $\tau^* = 20\%/4 = 5\%$.

Table 7 shows how our semi-elasticity estimates vary by the inclusion of controls for property and buyer/seller characteristics in the hedonic-logit model. For properties of all ages, our estimates of the semi-elasticity for one-year flips (ϵ_{1-year}) fall between 4.7 and 5.1, while those for the overall semi-elasticity (ϵ_{2-year}) fall between 3.7 and 4.8. Our preferred specification described in Section 4.2 yields $\epsilon_{1-year} = 5.1$ and $\epsilon_{2-year} = 3.7$. We obtain semi-elasticities which are around 50% higher for properties older than 5 years at time of sale, indicating that segments of the market which have experienced muted price growth – such as houses which are rapidly depreciating – are more sensitive to transfer taxes.

Our estimates generate an upper bound on τ^* for two main reasons. First, the missing mass estimates from our hedonic-logit bunching design underestimate short-term sales volume in the pre-reform period, meaning we also underestimate the amount of trades crowded out by the transfer tax. This biases the semi-elasticity downward, and hence, τ^* is biased upward. Second, our weather shock estimates of the non-fundamental share are intent-to-treat (ITT) in the sense that we do not know the true fraction of the 20% drop in volume that is due to noisy flippers. By assuming the entire drop in volume due to storm systems is from

TABLE 7. Sensitivity Analysis of Optimal Flat Tax Rate and Volume Semi-Elasticity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Property sample:	Full	Full	Full	Full	Full	Age $\geq$ 5	Age $\geq$ 10
τ^*_{1-year}	4.2%	4.3%	4.3%	3.9%	3.2%	2.6%	2.9%
τ^*_{2-year}	4.2%	4.3%	4.3%	5.4%	2.9%	2.2%	2.7%
$\Delta mass_{<720}$	$71,411^{***}$	$70,977^{***}$	$70,961^{***}$	$69,159^{***}$	$85,762^{***}$	$69,407^{***}$	$57,087^{***}$
	(3,196)	(2,870)	(2,880)	(2,962)	(2,892)	(2,369)	(2,111)
$\Delta mass_{\geq 720}$	$-28,488^{***}$	$-28,568^{***}$	$-28,592^{***}$	$-36,020^{***}$	$-25,888^{***}$	$-12,946^{***}$	$-16,091^{***}$
	(5,714)	(5,314)	(5,317)	(5,403)	(4,240)	(4,201)	(3,140)
$\Delta mass_{<365}$	$31,156^{***}$	$30,855^{***}$	$30,827^{***}$	$33,546^{***}$	$41,455^{***}$	$35,966^{***}$	$29,088^{***}$
	(2,384)	(2,134)	(2,136)	(2,273)	(1,754)	(1,626)	(1,469)
ϵ_{1-year}	4.8	4.7	4.7	5.1	6.3	7.7	6.8
ϵ_{2-year}	4.8	4.7	4.7	3.7	6.8	9.2	7.5
Property controls	✓	✓	✓	✓	✓	✓	✓
Buyer/seller wealth		✓					
Buyer/seller housing wealth			✓				
Realty dummy					✓		
Material FEs				✓	✓	✓	✓
Property use FEs				✓	✓	✓	✓
Time FEs				✓	✓	✓	✓
K-S stat	0.105	0.105	0.105	0.105	0.105	0.149	0.149
K-S p-value	0.858	0.858	0.858	0.858	0.858	0.444	0.444
N	12,163,977	12,163,977	12,163,977	12,163,977	11,939,191	8,281,861	7,171,456

Notes: The table shows robustness of our optimal tax rates and sales volume semi-elasticity estimates to logit models described by equations (4.2)–(4.4). The top two rows show the implied optimal transfer tax rate τ^* obtained from sufficient statistics equation (2.15), assuming the 20% noise trading share estimated in Section 5.2. Each specification includes a set of property controls consisting of the holding period length (in days), a quadratic in property age (measured from the construction date), floor space, land area, number of floors, and building floor dummies. Columns (2) and (3) control for the wealth quintiles of the buyer and seller as of the tax year prior to the reform. The set of time fixed effects includes dummies for day-of-week, week-of-month, month-of-year, and public holidays. Column (4) refers to our baseline specification which we describe in Section 4.2. ϵ_{1-year} equals the missing mass of one-year flips $\Delta mass_{<365}$ scaled by pre-reform average annual sales of properties held less than 365 days ($= 43,646$) divided by the 15% flip tax rate; ϵ_{2-year} equals total missing mass ($= \Delta mass_{<720} + \Delta mass_{\geq 720}$) scaled by pre-reform average annual sales ($= 89,765$) divided by the 10% flip tax rate. In the last two columns of the table we restrict to sales of properties $\geq$ 5 years old or $\geq$ 10 years old as of the sale date. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$ for the missing sales estimates, where we obtain standard errors using the bootstrap procedure of Chetty et al. (2011). For each specification, we report the test statistic and p-value for the Kolmogorov-Smirnov test of the null of equivalence between the data and model-implied distributions in the pre-reform period.

speculators delaying sales for at least several weeks after the tropical storm season subsides, we focus on a worst-case scenario from the policymaker's perspective. We derive a revised sufficient statistics formula in Appendix A.2 which depends on weather-induced search costs and find our baseline optimal tax estimates are biased further upward by, at most, 0.22 p.p.

6.2 Calibration of Investor Type-Specific Taxes

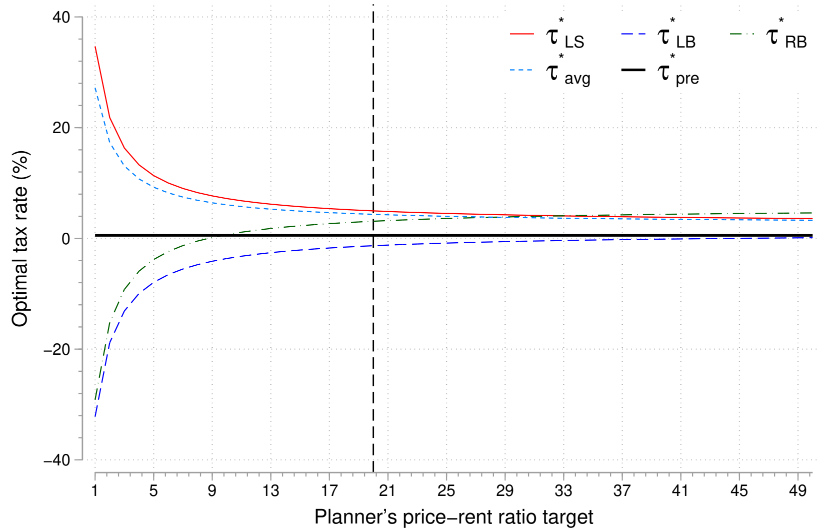
We now calibrate the version of our model where the policymaker imposes differential tax rates depending on the investor's housing demand, as is commonly done in global real estate markets. We defer the step-by-step calibration details to Appendix A.4, but offer a summary here. Recall from our conceptual framework in Section 2.2 the categorization of investors in the housing market into four groups based on their housing demands from equation (2.16): renter-sellers (RS), landlord-sellers (LS), renter-buyers (RB), and landlord-buyers (LB). To estimate the optimal tax rates for a group g of investors, we need three items: (i) the empirical share s_g of investors who fall into each group, (ii) the policymaker's beliefs about housing returns, $\mu_p^p + \mu_p^r$, and (iii) estimates of each group's beliefs about housing returns, $\mu_g^p + \mu_g^r$.

We sort taxpayers for whom we observe initial housing endowments $X_{i,0}$ and housing demands into the four groups $g \in \{RS, LS, RB, LB\}$. From the investment rule in equation (2.20), let Υ be the sum of mean observed prices and rents, or $\Upsilon \equiv \mu_p^p + \mu_p^r$. Setting the free parameter Υ equal to the expected payoff from the planner's perspective is consistent with a production economy in which investors own the developers who supply housing units to the market.[32] In our data, the vector of investor type shares is $\{s_{RS}, s_{LS}, s_{RB}, s_{LB}\} = \{2.14\%, 87.64\%, 2.84\%, 7.38\%\}$. The vast majority of housing transactions in our dataset originate from landlords, rather than renters climbing onto the housing ladder.

Unlike the sufficient statistics approach for a flat flip tax rate, an advantage to calibrating our model to a type-specific tax regime is that we do not need to take a stance on the appropriate measure of the *ex ante* share of noise trading in the market. At the same time, under a production economy, the τ_g^* are now a function of the planner's beliefs on what is the "correct" return to housing, or in other words, the policymaker's desired price-rent ratio target, μ_p^p/μ_p^r. In this sense, optimally choosing Tobin taxes on housing is akin to the macroprudential policy goal of improving the relative affordability of owning a home (He, Nier, & Kang 2016), which can further be motivated by concerns about risk spillovers to the financial sector through lending and mortgage derivatives markets. We solve for the set of optimal tax rates and equilibrium prices under different price-rent ratio targets by setting the planner's belief on the price level μ_p^p equal to the median home value in 2006, prior to the sharp increase in house prices documented in Figure 1. We continuously vary the belief on rents μ_p^r to trace out how the flip tax regime and price growth evolves with the ratio target.

[32]This is equivalent to setting $\Upsilon = \mathbb{E}_p[\widetilde{D}_i]$, which here is $\mathbb{E}_p[P_2 - H_{i,2}] = E_p[P_2 + r_2 \cdot (X_{i,1} - 1)]$, or the price less the housing cost, which includes the rental yield on housing above the owner-occupied scale.

FIGURE 7. Optimal Tax Rate Vector by Price-Rent Ratio Target



Notes: The figure plots the set of optimal tax rates by investor type with respect to the policymaker's price-rent ratio target. τ^*_{LS} and τ^*_{LB} refer to rates imposed on landlord-sellers and landlord-buyers, respectively, while τ^*_{RB} refers to the tax rate on renter-buyers who are renters on the margin of homeownership. The reference category is the renter-sellers, who in practice never pay taxes, as they rent and are on the margin of downsizing their rental unit. τ^*_{avg} is the share-weighted average of the optimal tax rates, while $\tau^*_{pre} = 0.55\%$ is the average tax rate paid across all taxpayers transacting a property in the pre-reform period, where the LS group pays an average rate of 0.59%, the LB group pays 0.36%, and the RB group pays 0.36%. See Appendix B for details on the pre-existing property tax regime.

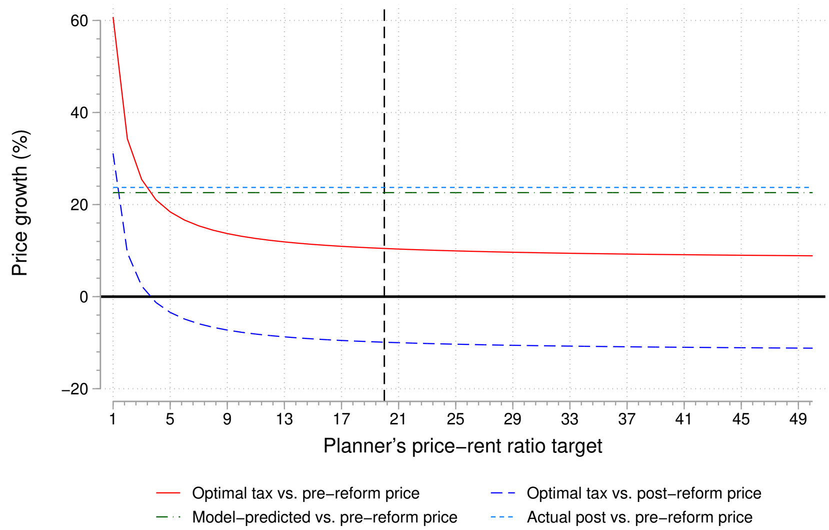
We then run the model-implied regression from equation (2.19) group-by-group, or:

$$\widehat{\Omega} \cdot X_{i\in g,t} + \widehat{\Omega}_{i\in g} = \alpha_{i\in g} \cdot P_t \times (1 + \mathcal{D}_{i\in g,t} \cdot \tau_{i\in g,t}) + e_{i\in g} \tag{6.1}$$

where $\widehat{\Omega}_{i\in g}$ and $\widehat{\Omega}$ are the empirical analogs of (2.8) and (2.9), respectively. From this regression, we recover taxpayer fixed effects α_i, which capture individual risk preferences. The interaction term $D_{i\in g,t} \cdot \tau_{i\in g,t}$ captures time-varying exposure to housing transfer taxes, which is jointly determined by buyer ($\mathcal{D}_{i,t} = 1$) or seller ($\mathcal{D}_{i,t} = -1$) status and the observed tax rates $\tau_{i\in g,t}$. The 2011 tax reform acts as a shock to τ_g which allows us to identify the fixed effect vector and calibrate the optimal group-specific taxes via formula (2.17).

We characterize the set of optimal tax rates in Figure 7. Lower price-rent ratio targets require higher tax rates on flippers and lower tax rates on buyers. For moderate price-rent ratio targets between 20 and 30, the tax rate imposed on the LB group is very close to 0%, indicating that within this group beliefs about property values align with those of the planner. For price-rent ratio targets less than 10, the optimal tax calls for purchase subsidies for both current and prospective homeowners. Regardless of the target, optimal implementation calls for a much higher average tax rate than the average 0.55% rate under the pre-existing regime

FIGURE 8. Price Growth Counterfactuals by Price-Rent Ratio Target



Notes: The figure shows how price levels under the optimal tax regime compare to price levels under counterfactual tax regimes. The solid red line plots implied price growth due to moving from the empirical pre-reform price level to the optimal tax regime with type-specific rates. The blue dashed line plots price growth due to moving from the empirical post-reform price level to the optimal tax regime. The green dashed line compares the model-predicted price when we impose the actual tax rates from the pre-reform period to the actual pre-reform price. The light blue dashed line compares the empirical post- and pre-reform prices.

(solid black line). For target ratios between 20 and 30, τ^*_{avg} ranges from 4.35% to 3.76%, in line with the optimal flat tax rates we calibrate via sufficient statistics in Table 7.

Policymakers often enact flip taxes to "cool the market" by crowding out speculation, which is a statement about lowering the equilibrium price *level* rather than improving the relative affordability of ownership. Figure 8 shows three ways in which flip taxes seldom achieve this objective. First the model predicts that imposing the transfer tax reform, as Taiwan did in 2011Q3, results in a large increase in house prices of 22.60% which almost matches the observed price growth of 23.73%. Second, prices are always higher under the optimal tax regime than the pre-existing tax regime, as the former features much higher average tax rates driven by taxes on flippers (solid red line). Third, moving from the post-reform regime, which levied a 15% rate on one-year flips, to the optimal tax vector (blue dashed line) results in lower prices for all price-rent ratio targets for which τ^*_{LS} is lower than the empirical average flip tax rate of approximately 13%.

In Appendix A.4, we show by evaluating equation (2.22) how the welfare gains from moving away from the actual tax regime to the optimal one are always positive for renters and negative for owners, and these welfare gains are virtually invariant to the choice of price-rent ratio target. Under a standard ratio target of 20, renters looking to buy (RB) realize a

66.43% increase in welfare, while the LS and LB groups experience welfare reductions of 64.61% and 11.45%, respectively. Intuitively, the existing tax regime accommodates very high price-rent ratios, such that renting is much more affordable than owning. Moving to the optimal regime involves spreading taxes out more evenly across the investor groups, resulting in a much higher average tax rate τ^*_{avg}, as pictured in Figure 7.

A more punitive tax regime induces homeowners to substitute towards renting, which moves the realized price-rent ratio down towards the target even as price levels rise, thus increasing the relative affordability of homeownership. More generally, prices in Figure 8 increase with the flip tax rate τ_{LS} in a convex fashion, since it becomes increasingly difficult to lower the price-rent ratio target through substitution to the rental market after so many trades have already been deterred. Our empirical results corroborate the strength of this substitution channel. Our findings on the distributional consequences of flip taxes complement recent work by Han, Ngai, & Sheedy (2022), who show through the lens of a housing search model that Toronto's sales surcharge of 1.3% levied on all properties generated a large deadweight loss by distorting choices in favor of renting and buying-to-let strategies. We instead study a Tobin tax regime which targets short-term investors, and consequently, we uncover muted effects on buy-to-let behavior, with rental yields increasing by only 0.52 basis points after the reform. This effect is driven by an increase in rental income among existing landlords rather than investors supplying new rental units to the market.[33]

Finally, we acknowledge the planner's objective function underlying our optimal tax formulas does not incorporate price stability, revenue constraints, or concerns about excessive leverage. Given the evidence we provide in Appendix C that housing prices overall increased after the reform, but fell by roughly 20% for bottom-tier apartments, normative concerns about housing consumption inequality (i.e. larger Pareto weights on renters) might justify higher optimal tax rates. However, as a price correction tool, our study supports the low, flat Tobin tax rates on housing transactions currently in place in many large property markets.

7 Conclusion

We estimate the optimal tax on speculative housing transactions. Investors decide whether to rent or own property and experience search frictions, in addition to facing rental income and capital gain risk. Leveraging administrative tax return data and a reform which levied

[33]In unreported results, we estimate difference-in-differences models at the taxpayer level in which treatment status is defined by whether the taxpayer owns multiple residential properties. The difference-in-differences coefficient for the probability of renting out property is a statistically insignificant 0.005 (p-value = 0.472).

a tax surcharge on sales of investment properties, we calibrate the model for two sets of available policy instruments: a uniform round-trip transaction tax (i.e. a canonical Tobin tax) and a vector of tax rates differentially targeting sellers vs. buyers and homeowners vs. renters. For the uniform tax, our model admits sufficient statistics formulas which imply an upper-bound optimal tax rate of 4%, justifying the flat tax rates already imposed in top global real estate markets. Allowing for separate taxes on flippers, current owners looking to buy, and renters, optimal transfer tax policy depends on the policymaker's desired price-rent ratio, and higher tax rates on flippers result in large welfare gains for the marginal renter.

We document both empirically and through the lens of our structural framework that higher Tobin tax rates render properties more illiquid and raise aggregate housing price levels. Taxes on flips can improve pricing efficiency but result in a lower price-rent ratio, which entails a large redistribution of wealth from sellers to buyers hoping to mount the housing ladder. Unprecedented investor demand for residential space induced by the COVID-19 pandemic has led to renewed interest in transfer taxes as a tool to promote housing affordability, especially in countries like the U.S. where housing policy is largely implemented at a local level. Given the challenges with using Tobin taxes to cool housing markets, we view causal empirical analysis of alternative policy instruments – such as loan-to-value (LTV) or debt-to-income (DTI) limits on mortgages – combined with structural work which models the microstructure of property markets as a promising route for future research.

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Online Appendix to

Flip or Flop? Tobin Taxes in the Real Estate Market

by Chun-Che Chi (Academia Sinica), Cameron LaPoint (Yale SOM), and Ming-Jen Lin (National Taiwan University)

A Optimal Transfer Tax Model Extensions

In this appendix, we provide details on the optimal tax framework from Section 2, including extensions where we incorporate housing search costs and discount rate heterogeneity. We derive formal linkages between the housing search costs version of our model and the weather shocks we use to recover the noise trading share estimated in Section 5.2.

A.1 Adding Housing Search Costs

We introduce search costs which capture the ease with which traders can find counterparts. Since sellers can list properties beforehand, only buyers are subject to this cost. We then recover a sufficient statistics formula featuring the same tradeoff as in (2.15), but with an added term that takes into account the idea that the presence of search frictions limits the role for corrective taxation in the presence of biased beliefs.

Specifically, we assume that buyers pay a search cost c_t per unit of floor space when they trade in period t. This leads to an amended expression for lifetime housing consumption:

$$\begin{aligned} C_{i,2} &= Y_{i,2} + P_2 \cdot X_{i,1} + P_1 \cdot (X_{i,0} - X_{i,1}) - \tau \cdot P_1 |\Delta X_{i,1}| + T_{i,1} \\ &- c_1 \cdot (X_{i,1} - X_{i,0}) \times \mathbb{1}\{X_{i,1} > X_{i,0}\} - H_{i,2} \end{aligned} \tag{A.1}$$

where $\mathbb{1}\{X_{i,1} > X_{i,0}\}$ indicates that only buyers pay a search cost. Hence, the revised maximization problem is:

$$\begin{aligned} \max_{X_{i,1}} \Bigg\{ & \Big[\mu_i^p - P_1 - A_i \cdot Cov(Y_{i,2}, P_2)\Big] \cdot X_{i,1} - \tau \cdot P_1 |\Delta X_{i,1}| \\ & - c_1 \cdot X_{i,1} \times \mathbb{1}\{X_{i,1} > X_{i,0}\} - \frac{A_i}{2} \cdot (X_{i,1}\sigma^p)^2 + RP_i \Bigg\} \end{aligned} \tag{A.2}$$

where the rental risk premium RP_i is defined as before in equation (2.6). Asset demands are also identical to those derived in equation (2.7), except there is an additional term in the denominator for the search cost which applies to buyers:

$$\Delta X_{i,1}^{+}(P_1) = \frac{(\mu_i^p + \mu_i^r) - A_i\Omega_i - P_1(1+\tau) - c_1}{A_i\Omega} - X_{i,0} \quad \text{if} \quad \Delta X_{i,1}^{+}(P_1) > 0 \tag{A.3}$$

Higher search costs deter buyers from purchasing housing. The equilibrium price is then given by the implicit function:

$$P_1 = \frac{\int_{i\in\mathcal{T}(P_1)} \left(\frac{\left(\mu_i^p + \mu_i^r\right)}{a_i} - A\left(\Omega_i + \Omega X_{0i}\right) \right) dF(i) - c_1 \left(\int_{i\in\mathcal{B}(P_1)} \frac{1}{a_i} dF(i) \right)}{1 + \tau \cdot \left(\int_{i\in\mathcal{B}(P_1)} \frac{1}{a_i} dF(i) - \int_{i\in\mathcal{S}(P_1)} \frac{1}{a_i} dF(i) \right)} \tag{A.4}$$

where $A \equiv (\int_{i\in\mathcal{T}(P_1)} A_i^{-1} dF(i))^{-1}$ and $a_i = A_i/A$. We again use the sets $\mathcal{T}$, $\mathcal{B}$, and $\mathcal{S}$ to denote investors who are traders, buyers, and sellers, respectively. Following Dávila (2021), we make a symmetry assumption regarding traders' preferences, the cross-sectional distribution of mean beliefs, hedging needs, and initial property holdings.

Assumption. *[S] (Symmetry) Traders have identical preferences, as indexed by $A_i = A$, $\forall i$. The cross-sectional distribution of traders' mean beliefs, hedging needs, and initial property holdings are symmetric: $(\mu_i^p + \mu_i^r) - A_i \cdot \Omega_i - A_i\Omega \cdot X_{i,0}$.*

Under Assumption $[S]$, the equilibrium price P_1 simplifies to:

$$P_1 = \int_{i\in\mathcal{T}(P_1)} \left(\frac{\left(\mu_i^p + \mu_i^r\right)}{a_i} - A\left(\Omega_i + \Omega \cdot Q\right) \right) dF(i) - c_1 \cdot \left\{ \frac{\int_{i\in\mathcal{B}(P_1)} dF(i)}{\int_{i\in\mathcal{T}(P_1)} dF(i)} \right\} = P_1^* - \tfrac{1}{2}c_1 \tag{A.5}$$

in which $Q \equiv \int X_{i,0} dF(i)$ is total housing supply, and $P_1^* \equiv \int_{i\in\mathcal{T}(P_1)} \Big(\left(\mu_i^p + \mu_i^r\right)/a_i - A\left(\Omega_i + \Omega \cdot Q\right) \Big) dF(i)$ is the equilibrium price in the absence of search costs. In this case, the price is independent of the tax. Intuitively, any jump in search costs discourages buyers from entering the market. Lower demand for housing then reduces the equilibrium price. The following lemma summarizes this result.

Lemma 2. *(Linear shock) Under assumption [S], the price when buyers pay a search cost P_1 is linear in the search cost c_1 and the price with no search cost P_1^* is such that $P_1 = P_1^* - c_1/2$.*

Symmetry is a useful benchmark, because shutting down heterogeneity in risk aversion results in equilibrium prices P_1^* which are invariant to the tax rate τ. In general, the housing price absent any search costs P_1^* will increase with τ whenever $\int_{i\in B(P_1^*)} \frac{1}{a_i} dF(i) \leq \int_{i\in S(P_1^*)} \frac{1}{a_i} dF(i)$, and decrease if this inequality is flipped. This condition says that prices increase whenever a tax hike reduces homeowners' willingness to sell more than it reduces buyers willingness to buy, reducing housing inventory and resulting in a liquidity crunch. At the aggregate housing market level, such a scenario conforms to the empirical behavior of prices in response to the Taiwan reform in Appendix C.

The linear shock property from **Lemma 2** is critical when analyzing the effect of weather shocks on future prices and trading volume. In what follows, we assume that the search cost $c_t = z_t \cdot w_t$ is a product of two independent components: $z_t \sim_i N(\mu_i^z, (\sigma^z)^2)$ which reflects heterogeneous investor beliefs, and time-dependent slack in the housing market $w_t = \phi \cdot w_{t-1} + \varepsilon_t^w$ which captures weather conditions. Bad weather implies a jump in ε_t^w.[1] In keeping with our empirical evidence (cf. Table 4) that severe weather conditions have persistent effects on trading volume, we model w_t as following an AR(1) process.

One might interpret w_t more generally as a persistent shock to housing search costs. The recent proliferation of iBuyers such as Opendoor in the U.S., which improve housing liquidity by giving homeowners "take it or leave it" offers (Buchak et al. 2021) would represent a scenario in which $\varepsilon_t^w < 0$. Under this formulation, one can think of bad weather as a negative shock to the arrival rate of buyers, which gradually recovers once weather conditions normalize. **Lemma 2** implies that beliefs about future prices include beliefs about the impact of weather on search frictions. For example, under a transitory (negative) weather shock with $\varepsilon_1^w > 0$ in period 1 and $\varepsilon_t^w = 0$ in period 2 onward, the mean of future prices is $\mathbb{E}_i[P_2] = \mu_i^p + \mathbb{E}_i[c_2]/2$, with $\mathbb{E}_i[c_2] = \phi \cdot \varepsilon_1^w \mu_i^z$ and $var(P_2) = (\sigma^p)^2 + (\phi \cdot \varepsilon_1^w \sigma^z/2)^2$.

We now proceed to derive a new sufficient statistics formula for the optimal transfer tax rate in the presence of weather-induced search costs. To do so, we apply the trading volume implementation in Dávila (2021), in which the policymaker sets the tax rate to completely eliminate any non-fundamental trading activity. We start by presenting an expression for trading volume and then show how to decompose aggregate volume into components induced by fundamental and non-fundamental traders, and any reductions in volume due to the tax regime τ and weather shocks. First, aggregate trading volume is:

$$P_1 V(\tau) = \kappa(P_1, \tau)\Bigg[\frac{1}{2}\int_{i\in\mathcal{T}(\tau)} \left(\left(-\frac{dX_{i,1}}{d\tau}\right)(\mu_i^s - A_i\Omega_i - P_1 sgn\,(\Delta X_{i,1})\,\tau \right. \\ \left. - A_i\Omega^s X_{i,0} dF(i) + c_1 \int_{i\in\mathcal{B}(\tau)} \frac{\partial X_{i,1}}{\partial\tau} dF(i)\right] \tag{A.6}$$

[1]This shock may not necessarily be a continuous function of proxies for weather conditions we consider in our empirical setting, such as rainfall or wind gusts. For instance, ε_t^w may be a dummy equal to one when a (local) weather condition attains some threshold (i.e. an official typhoon at ≥ 74 mph wind gusts).

$$\text{with} \quad \Omega^s = (\sigma^p)^2 + (\phi \cdot \varepsilon_1^w \sigma^z/2)^2 + (\sigma^r)^2 - 2Cov(P_2, r_2)$$
$$\mu_i^s = \mu_i^p + \phi \cdot \varepsilon_1^w \mu_i^z + \mu_i^r$$
$$\kappa(P_1, \tau) = (1 + \tau \cdot (d \log P_1/d\tau))^{-1}$$

Trading volume is decreasing in the search cost c_1 and the buyer's elasticity of owned property with respect to the tax. A transitory weather shock persistently affects the trading volume and equilibrium price via expectations of future housing prices that reflect heterogeneous beliefs about future search costs. Trading volume can be decomposed into:

$$P_1 V(\tau) = \Theta_F(\tau) + \Theta_{NF}(\tau) - \Theta_\tau(\tau) - \Theta_{WS}(\tau) \tag{A.7}$$

where the four components are defined as

$$\Theta_F(\tau) = \frac{\kappa(P_1, \tau)}{2} \int_{i \in \mathcal{T}(\tau)} \left(-\frac{dX_{i,1}}{d\tau} \right) (-A_i \Omega_i - A_i \Omega^s X_{i,0}) \, dF(i) \tag{A.8}$$

$$\Theta_{NF}(\tau) = \frac{\kappa(P_1, \tau)}{2} \int_{i \in \mathcal{T}(\tau)} \left(-\frac{dX_{i,1}}{d\tau} \right) \mu_i^s dF(i) \tag{A.9}$$

$$\Theta_\tau(\tau) = \frac{\kappa(P_1, \tau)}{2} \cdot \tau P_1 \int_{i \in \mathcal{T}(\tau)} \left(-\frac{dX_{i,1}}{d\tau} \right) sgn\,(\Delta X_{i,1}) \, dF(i) \tag{A.10}$$

$$\Theta_{WS}(\tau) = \kappa(P_1, \tau) c_1 \int_{i \in \mathcal{B}(\tau)} \left(-\frac{\partial X_{i,1}}{\partial \tau} \right) dF(i) \tag{A.11}$$

which represent, respectively, the fundamental volume $[F]$, non-fundamental volume $[NF]$, tax-induced volume reduction $[\tau]$, and weather-induced volume reduction $[WS]$. Under the symmetry assumption and the assumption that the market starts out with no excess demand or supply, we can simplify these expressions using the fact that $\kappa(P_1, \tau) = 1$.[2]

$$\Theta_F(\tau) = \frac{1}{2} \left| \frac{dX_{i,1}}{d\tau} \right| A \left(\int_{i \in \mathcal{S}(\tau)} \Omega_i dF(i) - \int_{i \in \mathcal{B}(\tau)} \Omega_i dF(i) \right)$$
$$\Theta_{NF}(\tau) = \frac{1}{2} \left| \frac{dX_{i,1}}{d\tau} \right| \left(\int_{i \in \mathcal{S}(\tau)} (\mu_i^p + \phi \cdot \varepsilon_1^w \mu_i^z + \mu_i^r) \, dF(i) - \int_{i \in \mathcal{B}(\tau)} (\mu_i^p + \phi \cdot \varepsilon_1^w \mu_i^z + \mu_i^r) \, dF(i) \right)$$
$$\Theta_\tau(\tau) = \tau P_1 \left| \frac{dX_{i,1}}{d\tau} \right| \int_{i \in B(\tau)} dF(i)$$

[2]That is, $\int_{i \in \mathcal{S}(\tau)} X_{i,0} dF(i) = \int_{i \in \mathcal{B}(\tau)} X_{i,0} dF(i)$. This initial condition is guaranteed under the assumption that investors have Gaussian trading motives.

$$\Theta_{WS}(\tau) = -z_1\left(\phi \cdot w_0 + \varepsilon_1^w\right)\frac{dX_{i,1}}{d\tau}\int_{i\in\mathcal{B}(\tau)} dF(i),$$

where we take $\left|\frac{dX_{i,1}}{d\tau}\right| = \frac{P_1}{A\cdot var[\widetilde{D}]}$ outside of the integrals because it is constant across investors under the symmetry assumption [S]. Under symmetry, $dP_1/d\tau = 0$, and therefore the total derivative of housing demand with respect to the tax is equal to the partial derivative:

$$\frac{dX_{i,1}}{d\tau} = \frac{\partial X_{i,1}}{\partial\tau} + \cancel{\frac{\partial X_{i,1}}{\partial P_1}\cdot\frac{dP_1}{d\tau}} = \frac{\partial X_{i,1}}{\partial\tau}$$

The weather shock ε_1^w only affects Θ_{WS} and Θ_{NF} via the expected price. The following lemma summarizes this result:

Lemma 3. *(Weather does not affect fundamental trades) Under Assumption [S], changes in trading volume due to ε_1^w are not due to changes in fundamental volume if buyers and sellers start with the same aggregate housing endowment: $\int_{i\in\mathcal{S}(\tau)} X_{i,0}dF(i) = \int_{i\in\mathcal{B}(\tau)} X_{i,0}dF(i)$.*

We are now ready to characterize the optimal tax rate with weather-induced search costs. The certainty equivalent of investor i from the planner's perspective is given by:

$$V_i^p(\tau) = \Big[\left(\mu_p^p + \phi\cdot\varepsilon_1^w\mu_p^z + \mu_p^r\right) - P_1 - \Omega_i - c_1\cdot\mathbb{1}\{X_{i,1} > X_{i,0}\}\Big]X_{i,1}(\tau)$$
$$+ P_1(\tau)X_{i,0} - \frac{A_i}{2}\Omega\left(X_{i,1}(\tau)\right)^2 + \widetilde{T}_{i,1}(\tau) - \mu_p^r \tag{A.12}$$

The optimal tax satisfies $\int_{i\in\mathcal{T}(\tau)}(dV_i^p/d\tau)dF(i) = 0$, leading to the optimality condition:

$$\int_{i\in\mathcal{T}(\tau)}\left(-\frac{dX_{1i}}{d\tau}\right)\mu_i^s dF(i) = \tau P_1\int_{i\in\mathcal{T}(\tau)}\left(-\frac{dX_{i,1}}{d\tau}\right) sgn\left(\Delta X_{i,1}\right)dF(i) + c_1\cdot\int_{i\in\mathcal{B}(\tau)}\frac{dX_{i,1}}{d\tau}dF(i) \tag{A.13}$$

Using our decomposition of aggregate trading volume from (A.7), we can use this condition to write the optimal tax rate as a function of the share of non-fundamental trades $s_{NF} = \Theta_{NF}/P_1V$, the semi-elasticity of volume with respect to the tax, and the search cost as a fraction of home values.

$$\Theta_{NF}(\tau) = \Theta_\tau(\tau) - \frac{1}{2}\Theta_{WS}(\tau) \tag{A.14}$$
$$= -\kappa(P_1,\tau)\tau P_1\frac{dV}{d\tau} - \frac{\kappa(P_1,\tau)}{2}c_1\frac{dV}{d\tau} \tag{A.15}$$
$$\implies \frac{\Theta_{NF}(\tau^*)}{P_1(\tau^*)V(\tau^*)} = -\kappa(P_1,\tau^*)\left(\tau^* + \frac{1}{2}\frac{c_1}{p_1}\right)\frac{d\log V}{d\tau}|_{\tau^*} \tag{A.16}$$

$$\implies \tau^* = \frac{\frac{\Theta_{NF}(\tau^*)}{P_1(\tau^*)V(\tau^*)}}{-\kappa(P_1,\tau^*)\frac{d\log V}{d\tau}|_{\tau^*}} - \frac{1}{2}\frac{c_1}{P_1} \tag{A.17}$$

Using the small-tax approximation around τ^*, the revised sufficient statistics formula is:

$$\tau^* \approx -\frac{\frac{\Theta_{NF}(0)}{P_1(0)V(0)}}{\frac{d\log V}{d\tau}|_{\tau=0}} - \frac{1}{2}\frac{c_1}{P_1} \equiv \frac{s_{NF}\{\tau=0\}}{\frac{d\log V}{d\tau}|_{\tau=0}} - \frac{1}{2}\frac{c_1}{P_1} \tag{A.18}$$

where the tax rate is decreasing in the search cost. Intuitively, bad weather (or any market friction which raises the search cost to buyers), deters noisy trades, and thus a lower tax rate is needed to implement the Pigouvian approach to mitigating speculation.

A.2 Optimal Tax Estimates with Weather Shocks

In Section 5.2, we use severe weather shocks to identify the share of housing transfers which are due to noise trading. We now formalize the conditions under which weather-induced search frictions in the housing market are informative about speculative beliefs.

A consequence of the new sufficient statistics formula in (A.18) is that when search costs are small relative to the price of housing ($c_1/P_1 \to 0$), we recover the original sufficient statistics formula. In our empirical context, we propose daily frequency time series regressions of deviations of aggregate home sale volume from long-run trend (e.g. a six-month moving average as in Section 5.2) on weather shocks of the following form:

$$Volume_t = \beta \cdot Weather_t + \delta_t + \varepsilon_t^w \tag{A.19}$$

where δ_t are week-year and day of week fixed effects to absorb high and low-frequency seasonality in the housing market, and $Weather_t$ is a weather condition such as a dummy for whether market experiences a tropical storm or severe rainfall. The coefficient $\widehat{\beta}$ obtained from this regression does not directly pin down the non-fundamental volume share s_{NF}; it is contaminated by the effect of weather on buyer search costs.

From the decomposition in (A.7) we can relate $\widehat{\beta}$ to volume shares via

$$\widehat{s}_{NF} = \widehat{\beta} - \widehat{s}_{WS} \tag{A.20}$$

To see why, consider long-run average sales volume $\overline{V}$ around a point where $\varepsilon^w = 0$, or a point at which weather conditions are at their long-run trend:

$$\overline{V} = \Theta_F(\varepsilon^w = 0) + \Theta_{NF}(\varepsilon^w = 0) - \Theta_\tau(\varepsilon^w = 0) - \Theta_{WS}(\varepsilon^w = 0) \tag{A.21}$$

Now consider a transitory negative weather shock $\varepsilon_1^w = 1$. For instance, if $\varepsilon_t^w \sim N(0, 1/2)$, then this is equivalent to the rainfall shock that corresponds to the typical tropical storm event in our empirical setting. From equation (A.8) we have that:

$$\frac{\partial V}{\partial \varepsilon_1^w} = \frac{\partial (V - \overline{V})}{\partial \varepsilon_1^w} = \frac{1}{P_1} \cdot \left[\Theta_{NF}(\varepsilon_1^w) - \Theta_{WS}(\varepsilon_1^w) \right] \tag{A.22}$$

$$\implies \frac{\partial V/V}{\partial \varepsilon_1^w} = \frac{1}{P_1 \cdot V} \cdot \left[\Theta_{NF}(\varepsilon_1^w) - \Theta_{WS}(\varepsilon_1^w) \right] \tag{A.23}$$

$$= s_{NF}(\varepsilon_1^w) - \underbrace{s_{WS}(\varepsilon_1^w = 1)}_{\propto c_1/p_1} \tag{A.24}$$

Since $\widehat{s}_{WS} \propto c_1/P_1$, it follows from (A.19) that as weather-induced search costs become small relative to home values (i.e. $c_1/P_1 \to 0$), $\widehat{\beta}$ from our weather regressions becomes a better proxy for the non-fundamental trading share:

$$\lim_{c_1/P_1 \to 0} \tau^* = \frac{\widehat{\beta}}{-\frac{d \log V}{d\tau}\big|_{\tau=0}} \tag{A.25}$$

Or, put another way, using $\widehat{\beta}$ from a regression in the tax regime where $\tau = 0$ is an empirical proxy for the non-fundamental trading share s_{NF} produces an upper-bound estimate of the optimal Tobin tax rate, because time variation from ε_t^w identifies changes in volume due to non-fundamental traders exiting the market and increased search costs that make it harder for buyers to match with sellers.[3]

How sharp is this upper bound? As a back-of-the-envelope exercise, we parameterize this search cost by running regressions of the form:

$$TOM_t = \gamma \cdot Weather_t + \delta_t + \varepsilon_t^w \tag{A.26}$$

where the outcome variable is time on market (TOM) in the pre-reform period ($\tau = 0$) for properties from a large home listing service (see Appendix D). $\widehat{\gamma}$ from this regression identifies the effect of the same weather shock we use to identify $\widehat{\beta}$ on buyer-seller matching, measured in days. We obtain estimates of $\widehat{\gamma}$ between 20 and 21 days for our most conservative specification that defines $Weather_t$ as a "rainy season" dummy equal to unity when the 4-week moving average of cumulative daily rainfall during the peak storm months of July,

[3] We use log deviations from six-month moving average volume as our outcome in Section 5.2. We recover the same optimal tax conditions with "hat algebra," where $\widehat{\beta} = \frac{\partial \log \widehat{V}/\widehat{V}}{\partial \varepsilon_1^w} = \widehat{s}_{NF}(\varepsilon_1^w = 1) - \widehat{s}_{WS}(\varepsilon_1^w = 1)$.

August, and September exceeds average daily rainfall during the calendar year.[4]

Using Census monthly wages, we then convert this estimate from units of time to a monetary value to pin down c_1. During the time period of our listing data, the median regular monthly wage (exclusive of fringe benefits) was 36,687 NTD compared to a median transaction value of roughly 7 million NTD, implying a search cost of 0.36% of market housing value.[5] Compared to our preferred estimate of $\tau^* = 4\%$ which ignores search costs, accounting for search costs attenuates our estimated optimal Tobin tax by only $(0.36/2)/5 + (0.36/2) = 0.216$ p.p. Thus, the original sufficient statistics formula of Dávila (2021) delivers a close approximation to the optimal tax rate in the presence of housing search costs.

A.3 Adding Heterogeneity in Investment Horizon

As we show in Section 5.2, weather shocks such as severe storm and heavy rainfall crowd out short-term sales but not transactions with other tags such as out-of-town investors commonly invoked in the literature to identify noise traders. This supports using holding period length as a way to target speculators, as the government did in our empirical application to the transfer tax surcharge in Taiwan. Here we explore the extent to which heterogeneity in investment horizon might be a source of pricing inefficiencies separate from the biased beliefs about fundamentals which is the impetus for corrective taxation in our baseline model.

We retain the model setup of Section 2, except now investors have expected utility:

$$\mathbb{E}_i\Big[\beta_i \cdot U_i(C_{i,2})\Big] \quad \text{with} \quad U_i(C_{i,2}) = \exp\{A_i \cdot C_{i,2}\} \tag{A.27}$$

where we have placed the investor's discount factor β_i within the expectation operator. Uncertainty about the future discount rate on housing investments allows us to retain the empirical tractability of our two-period setup while accounting for the fact that investors may tradeoff between current and future marginal utility of consumption out of housing wealth in different ways. Modeling holding period heterogeneity via discount rate uncertainty is consistent with recent empirical evidence provided in Bessembinder & Décaire (2021) that bias in NPV estimates affects investment behavior and corporate profitability.

As before, we assume future prices, rents, and income are normally distributed, with $P_2 \sim_i \mathcal{N}\Big(\mu_i^P, (\sigma^P)^2\Big), r_2 \sim_i \mathcal{N}\Big(\mu_i^r, (\sigma^r)^2\Big)$, $Y_{i,2} \sim_i \mathcal{N}\Big(\mu_i^Y, (\sigma^Y)^2\Big)$, respectively. Therefore log

[4] Our calibration is conservative in that if we saturate the RHS of the TOM market regression with controls capturing property quality, such as property age, floor space, initial appraisal value, floor number, and land area, $\widehat{\gamma}$ becomes smaller and ceases to be statistically significant.

[5] We retrieve monthly wages from the Earnings and Productivity tables at Taiwan National Statistics. We describe the home listings data and how we computed TOM in Appendix D.

utility is normally distributed $A_i \cdot C_{i,2} \sim \mathcal{N}\Big(\mu_i^C, (\sigma_i^C)^2\Big)$, and we can write the moments as:

$$\mu_i^C = A_i \cdot \Big(\mu_i^Y + X_{i,1}\mu_i^P + P_1(X_{i,0} - X_{i,1}) - \tau P_1|\Delta X_{i,1}| + T_{i,1} - (1 - X_{i,1})\mu_i^r\Big) \tag{A.28}$$

$$\begin{aligned}(\sigma_i^C) &= A_i^2 \cdot \Big[(X_{i,1} \cdot (\sigma^P)^2 + (1 - X_{i,1})\sigma^r)^2 + (\sigma^Y)^2 + 2X_{i,1} \cdot Cov(Y_{i,2}, P_2) \\ &- 2(1 - X_{i,1})(X_{i,1} \cdot Cov(P_2, r_2) + Cov(Y_{i,2}, r_2))\Big]\end{aligned} \tag{A.29}$$

If we further assume discount factors are log-normally distributed, $\log(\beta_i) \sim_i \mathcal{N}\Big(\mu_i^\beta, (\sigma_i^\beta)^2\Big)$, then discounted utility is log-normally distributed via:

$$\log(\beta_i \cdot \exp(A_i \cdot C_{i,2})\Big) \sim_i \mathcal{N}\Big(\mu_i^\beta + \mu_i^C, (\sigma_i^\beta)^2 + (\sigma_i^C)^2 + 2\rho_i^{\beta,C} \cdot \sigma_i^\beta \sigma_i^C\Big) \tag{A.30}$$

where $\rho_i^{B,C}$ is the correlation coefficient between individual consumption and the discount factor. To illustrate how discount rate heterogeneity generates an extra component of speculative volume, we make the simplifying assumption that β_i and log utility are jointly correlated in proportion to the ratio of their variances:

$$\rho_i^{\beta,C} = \frac{\phi_i}{2} \cdot \frac{\sigma_i^C}{\sigma_i^\beta} \implies Cov(\beta_i, A_i \cdot C_{i,2}) = \frac{\phi_i \cdot (\sigma_i^C)^2}{2} \tag{A.31}$$

This assumption means that the discount factor, and therefore the housing investment horizon, positively co-moves in proportion to consumption risk $(\sigma_i^C)^2$. In other words, investors who face a more volatile consumption profile adopt a lower discount rate and behave more conservatively when deciding today on their housing demand $X_{1,i}$.

We can now write the housing demand function analogously to equation (2.7) where we replace the coefficient of absolute risk aversion A_i with $\widetilde{A}_i = \phi_i \cdot A_i$

$$\Delta X_{i,1}(P_1) = \begin{cases} \Delta X_{i,1}^+(P_1) = \frac{(\mu_i^p + \mu_i^r) - \widetilde{A}_i\Omega_i - P_1(1+\tau)}{\widetilde{A}_i\Omega} - X_{i,0} & \text{if } \Delta X_{i,1}^+(P_1) > 0 \\ 0 & \text{if } \Delta X_{i,1}^+(P_1) \leq 0, \Delta X_{i,1}^-(P_1) \geq 0 \\ \Delta X_{i,1}^-(P_1) = \frac{(\mu_i^p + \mu_i^r) - \widetilde{A}_i\Omega_i - P_1(1-\tau)}{\widetilde{A}_i\Omega} - X_{i,0} & \text{if } \Delta X_{i,1}^-(P_1) < 0 \end{cases} \tag{A.32}$$

and the variance-covariance structure terms Ω_i and Ω are defined as in equations (2.8) and (2.9). When ϕ_i increases, discounted marginal utility $\beta_i \cdot U_i'(C_{i,2})$ of future consumption decreases, and investors purchase less housing for consumption out of future profits. This is a direct implication of the stochastic discount factor $\mathbb{E}_i[\beta_i \cdot U'(C_{i,2})]/U_i'(C_{i,1})$ that arises here as it does in a standard dynamic consumption-savings problem.

We can also write the investor's and aggregate certainty equivalent CE from the planner's perspective as in (2.12) and (2.13), but again with $\widetilde{A}_i$ substituted for A_i. The individual marginal welfare impact of τ is given by:

$$\frac{dCE_i^p}{d\tau} = \Bigg[\underbrace{(\mu_p^p + \mu_p^r) - (\mu_i^p + \mu_i^r)}_{\text{Wedge of beliefs on returns}} + sgn\left(\Delta X_{1i}(\tau)\right) \cdot P_1(\tau) \cdot \tau - \underbrace{\left(1 - \frac{\phi_p}{\phi_i}\right) P_1(\tau)}_{\text{Wedge of beliefs on discount rates}} \Bigg] \cdot \frac{dX_{1i}(\tau)}{d\tau} - \underbrace{\Delta X_{1i}(\tau)\frac{dP_1(\tau)}{d\tau} + \frac{d\tilde{T}_{1i}(\tau)}{d\tau}}_{\text{Distributive externality}} \tag{A.33}$$

where ϕ_p is the planner's belief on the coefficient of correlation between the investor's consumption and their discount rate. All other terms in (A.34) are defined as in the baseline model of Section 2. The optimal uniform tax rate τ^* satisfies $\int_{i \in \mathcal{T}(i)} \frac{dCE_i^p}{d\tau} dF(i) = 0$, or:

$$\int_{i \in \mathcal{T}(\tau)} \left[-\left(\mu_i^p + \mu_i^r\right) + sgn\left(\Delta X_{1i}(\tau)\right) P_1(\tau)\tau - \left(1 - \frac{\phi_p}{\phi_i}\right) P_1(\tau) \frac{dX_{1i}(\tau)}{d\tau} \right] dF(i) = 0 \tag{A.34}$$

The above expression shows that the optimal tax sets the sum of the cumulative wedge between the policymaker and individual discount rate beliefs and individual beliefs about prices and rents equal to zero.

Unlike the sufficient statistics result we derive in **Lemma 1**, where the planner's beliefs about prices and rents, μ_p^p and μ_p^r, do not enter into the optimal tax formula, equation (A.34) shows that the planner's belief about the discount rate ϕ_p influences the optimal tax rate. This leads us to the following lemma which characterizes the optimal uniform flip tax as the tax rate eliminating any gap in expected returns between buyers and sellers.

Lemma 4. *(Optimal uniform flip tax under discount rate heterogeneity)*

(i) The optimal tax equals the gap between weighted average buyer and seller returns:

$$\tau^* = \frac{\mathcal{R}_{\mathcal{B}(\tau^*)} - \mathcal{R}_{\mathcal{S}(\tau^*)}}{2}$$

with $\mathcal{R}_{B(\tau)} = \int_{i \in B(\tau)} \omega_i^{\mathcal{B}}(\tau) \left(\frac{\mu_i^p + \mu_i^r}{P_1} + \frac{\phi_i - \phi_p}{\phi_p} \right) dF(i)$ *and* $\omega_i^{\mathcal{B}}(\tau) \equiv \frac{\frac{dX_{1i}(\tau)}{d\tau}}{\int_{i \in \mathcal{B}(\tau)} \frac{dX_{1i}(\tau)}{d\tau} dF(i)}$

with an analogous definition for sellers $i \in \mathcal{S}(\tau)$ *with weights* $\omega_i^{\mathcal{S}}$

(ii) In the special case where biased beliefs on prices/rents are identical across agents and

$\sigma^\beta \to 0$ (i.e. little discount rate uncertainty), the optimal tax reduces to:

$$\tau^* = \frac{\int_{i\in\mathcal{B}(\tau^*)} \omega_i^{\mathcal{B}}(\tau)\frac{\phi_i}{\phi_p} dF(i) - \int_{i\in\mathcal{S}(\tau^*)} \omega_i^{\mathcal{S}}\frac{\phi_i}{\phi_p} dF(i)}{2}$$

The first part of **Lemma 4** says that the optimal uniform tax rate is determined by the gap between buyers' $\mathcal{B}(\tau^*)$ and sellers' $\mathcal{S}(\tau^*)$ housing expenditure share-weighted average beliefs about the holding period return $(\mu_i^p + \mu_i^r)/P_1$ and percent deviations from the policymaker's discount rate $(\phi_i - \phi_p)/\phi_p$. The second part of the lemma shows that the portion of the corrective tax due to biased beliefs about discounting (i.e. propensity to flip) is zero when all parties agree on the discount rate, or $\phi_i = \phi_p$. In the case where individual consumption and discount factors are more correlated than what agents perceive, $\phi_p > \phi_i, \forall i$, then τ^* is a tax designed to encourage investors to hold onto properties to extract future consumption. In contrast, τ^* would be a uniform purchase subsidy if $\phi_p < \phi_i, \forall i$.

How important are differences in the horizon of speculative housing investments for the optimal corrective tax? To answer this question, we propose a simple empirical decomposition which compares the calibrated optimal uniform tax under our baseline model in Section 2, which features only heterogeneous beliefs about fundamental values, to the preceding model version with both heterogeneous beliefs and discount rate uncertainty.

We start by noting that in the baseline model, the optimal uniform tax rate τ^*_{base} can be characterized by the same gap in expected returns formula as in **Lemma 4**, except that the expected returns depend only on the wedge in beliefs about fundamentals, not the discount rate wedge $(\phi_i - \phi_p)$:

$$\tau^*_{base} = \frac{\mathcal{R}_{\mathcal{B}(\tau^*_{base})} - \mathcal{R}_{\mathcal{S}(\tau^*_{base})}}{2} \tag{A.35}$$

$$\text{with} \quad \mathcal{R}_{B(\tau_{base})} = \int_{i\in B(\tau_{base})} \omega_i^{\mathcal{B}}(\tau_{base}) \left(\frac{\mathbb{E}_i[\widetilde{D_i}]}{P_1}\right) dF(i) \tag{A.36}$$

$$\text{and} \quad \omega_i^{\mathcal{B}}(\tau_{base}) \equiv \frac{\frac{dX_{1i}(\tau)}{d\tau}}{\int_{i\in\mathcal{B}(\tau_{base})} \frac{dX_{1i}(\tau)}{d\tau} dF(i)}$$

where $\widetilde{D_i}$ is the capital gain on flipping housing, net of rental dividend (or cost) $H_{i,2}$, as defined in (2.3). **Lemma 1** shows that (A.35) can be characterized by the familiar sufficient statistics formula of *ex ante* non-fundamental volume share divided by volume semi-elasticity. Combining these results, we can express the difference in optimal tax rates with and without the role of discount heterogeneity on pricing inefficiency as follows:

$$\tau^*_{disc} - \tau^*_{base} = \frac{\mathcal{R}_{\mathcal{B}(\tau^*_{disc})} - \mathcal{R}_{\mathcal{S}(\tau^*_{disc})}}{2} - \left\{ \frac{s_{NF}\{\tau = 0\}}{\frac{-d\log V}{d\tau}\Big|_{\tau=0}} \right\} \tag{A.37}$$

We empirically identify the volume semi-elasticity $\varepsilon = d\log V/d\tau$ in Section 4.2 and estimate it to be 5.1 (see Table 7 for details); combined with our estimate of $s_{NF} = 20\%$ in Section 5.2 we estimate $\tau^*_{base} = 3.9\%$. To obtain τ^*_{disc}, we compare across observed counterparty pairs in the pre-reform period the average annualized (net-of-tax) expected returns of buyers to average realized returns among sellers, or in the model notation:

$$\tau^*_{disc} = \frac{1}{2 \cdot |\mathcal{B}|} \left[\int_{i\in\mathcal{B}(\tau)} \int_h \widetilde{r^i_h} \cdot G(h)di - \int_{i\in\mathcal{S}(\tau)} \widetilde{r^i} \cdot di \right] \tag{A.38}$$

where $\widetilde{r^i}$ indicates the annualized holding period return residualized on taxpayer characteristics as in Figure 4 with raw returns computed according to (5.1) and (5.2). Residualizing returns on investor characteristics approximates **Assumption** *[S] (Symmetry)*, which imposes $A \equiv A_i, \forall i$, or constant coefficients of absolute risk aversion in the cross-section of investors. We need *[S]* for the equality in (A.38) to hold. For buyers, we compute the expected value by integrating over the pdf of holding period returns $G(h)$, where the holding period length h maps to individual beliefs of discount rates ϕ_i via (A.36).

From estimating (A.38), we find $\tau^*_{disc} = 4.50\%$, with buyers' annualized average expected returns equal to 13.53%, and sellers' annualized average returns equal to 4.54%. Compared to $\tau^*_{base} = 3.90\%$, this implies heterogeneity in beliefs about fundamental values account for $3.90/4.50 = 86.67\%$ of the optimal corrective tax, while heterogeneity in discounting accounts for the residual 0.60 p.p.

A.4 Calibration & Counterfactual Pricing Analysis

In Section 6.2 we show how optimal investor-specific taxes vary according to the policymaker's desired price-rent ratio target. We calibrate according to the following steps:

1. We compute the common and investor-specific variance-covariance terms, $\widehat{\Omega}$ and $\widehat{\Omega}_i$ used in the regression in (2.19), and which capture investors' hedging needs. We use average housing prices and annual rental income to compute the covariance term $Cov(P_2, r_2)$ in (2.9). For the investor-specific covariance terms $Cov(Y_{i,2}, P_2)$ and $Cov(Y_{i,2}, r_2)$ in (2.8), we use each taxpayer's pre-tax annual taxable income as a proxy for the stochastic endowment $Y_{i,2}$. For this exercise, we restrict to years 2006 – 2013.

We exclude the post-2014 period to avoid a reform which imposed loan-to-value (LTV) limits for high-end investment properties in certain regions.

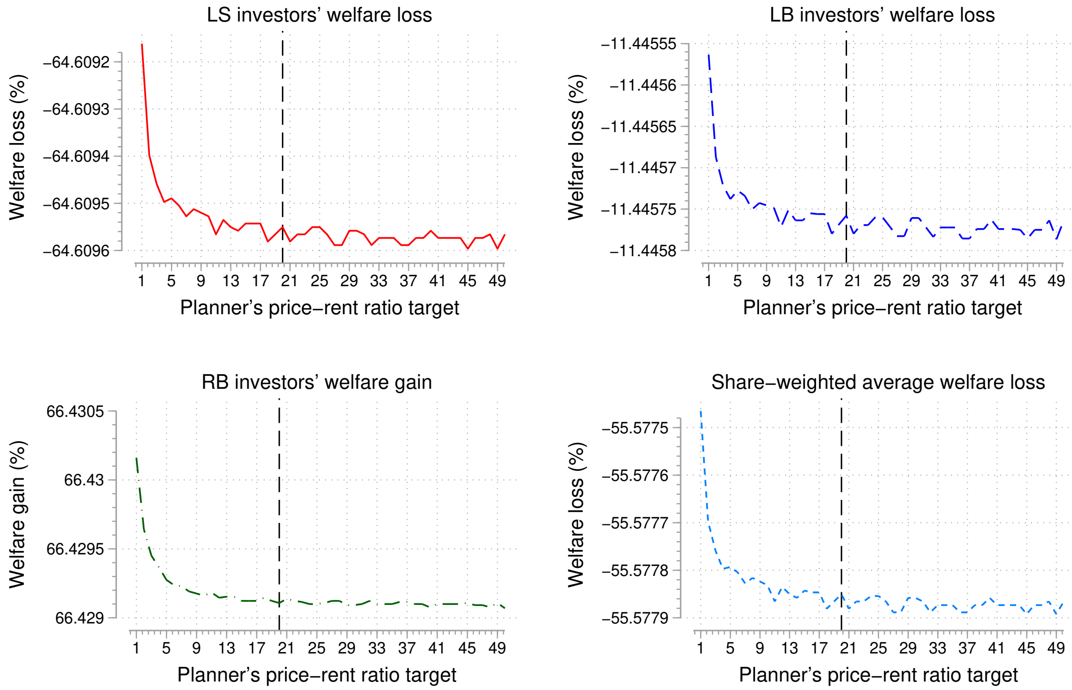
2. We compute the vector of actual tax rates faced by each investor in Taiwan before the transfer tax hike. We describe the full set of housing tax schedules in Appendix B.
3. We estimate the model-implied regression in equation (2.19), using the average market-wide price P_t in a given year, and the investor-specific tax rate τ_i calculated in the previous step. $P_t \cdot \tau_i$ yields a measure of investors' potential exposure to subsequent changes in the tax regime. From this regression we recover the individual fixed effects $\widehat{\alpha}_i$, which capture individuals' beliefs and risk preferences.
4. Using the estimated investor fixed effects, we rearrange equation (2.21) to estimate the market-clearing price under the optimal tax regime, $\widehat{P}$. We set Υ to be the sum of mean observed prices and rents, or $\Upsilon \equiv \mu_p^p + \mu_p^r$. Setting the free parameter Υ equal to the expected payoff from the planner's perspective is consistent with a production economy in which investors own the developers who supply housing units to the market.
5. Next, we plug $\widehat{P}, \widehat{A}_i, \widehat{\Omega}, \widehat{\Omega}_i$ into (2.20) to retrieve counterfactual housing demand $X_i(\tau_i^*)$ under the optimal tax rates τ_i^* for each individual investor i.
6. We then sort taxpayers into the four investor types from equation (2.16) based on their housing positions $X_i(\tau_i^*) - X_{i,0}$, where we take $X_{i,0}$ to be investors' initial housing endowment within our sample period. We use the renter-sellers (RS) as the reference category, since such investors are never subjected to transfer taxes.
7. Finally, we run the group-by-group regression (6.1) to recover a vector of group-specific beliefs $\widehat{\alpha}_g$ and plug these into (2.18) to obtain optimal tax rates for each group.

Supplementing the counterfactual results presented in Figure 7 and Figure 8, we show how welfare losses/gains vary across a continuous array of price-rent ratio policy targets in Figure A.1. We use the aforementioned steps to estimate equation (2.22) for each investor type g. This exercise compares welfare for each group under the optimal tax regime τ_g^* to that under the actual (post-reform) tax regime τ_g. For all groups, welfare improvements non-monotonically decline with the price-rent ratio target. Marginal renters always gain from moving to the optimal regime, while incumbent homeowners always lose. However, these movements in the welfare gains/losses are quantitatively trivial; moving from a price-rent ratio target of 1 to 50 increases the aggregate welfare loss by 8.41 $\times 10^{-6}$ p.p.

B Details on Taiwan's Property Tax System

In this appendix, we discuss the administration of Taiwan's property tax system, as outlined in Section 3.1. Before and after the enactment of the transfer tax surcharge we study, there

FIGURE A.1. Welfare Changes when Moving from Actual to Optimal Tax Regime



Notes: The figure shows how welfare gains and losses for each investor type vary with the policymaker's price-rent ratio target, according to our estimation of equation (2.22). In the bottom right panel, we compute the aggregate welfare loss by taking the share-weighted average of the gains/losses across the three investor types: landlord-sellers (LS), landlord-buyers (LB), and renter-buyers (RB), as defined by equation (2.16).

are six other tax bases related to housing. We compute these tax rates to calibrate the version of our structural model with investor-specific taxes in Section 6.2.[6]

(i) *Building property tax* (paid by owners): 1.2% to 5% of the appraised building value, depending on whether the house is self-occupied, the number of houses the taxpayer holds, and whether the property is residential or commercial use. Building appraisals occur once every three years.

(ii) *Land value tax* (paid by owners): progressive tax ranging from 1% to 5.5% of the "announced land value," which is an appraised value based on land transactions occurring in the area within the past three years.

(iii) *Deed tax* (paid by buyers at the time of sale): 6% of the appraised value of the property. Property appraisals are conducted by the government once every three years.

(iv) *Stamp duty tax* (paid by buyers at the time of sale): 0.1% of the sum of the appraised building value and "current land value" (CLV). The CLV is reassessed annually and based on recent transactions in the area.

[6]The formulas and tax brackets are described in the Ministry of Finance Tax Manual, available here.

(v) *Land value increment tax* (paid by sellers at the time of sale): 10% tax on CLV for sales of owner-occupied homes. Otherwise, this is a flat tax on a fraction (between 0 and 1, but close to 0.3 on average) of the CLV, with tax rates weakly decreasing in the holding period and ranging between 20% to 40%.

(vi) *House transfer income tax* (paid by sellers at the time of sale): liability is determined by the seller's personal income tax bracket and a local scale factor applied to transfer income, ranging from 0.08 for rural districts to 0.37 for the capital city of Taipei.

From the seller's perspective, there are five main steps to transferring property ownership.

1. Signing the contract and providing documents to the state to identify parties in the transaction and the new owner. The buyer pays the 0.1% stamp duty tax and a "contract fee" equal to 5-10% of the transaction price (1 to 3 days). The contract fee is then held in escrow until the sale closes.
2. Sellers file a transaction tax return and wait for the official tax document which lists the total payment due. The document usually arrives within 7 to 21 days.
3. Sellers pay transaction taxes and capital gains tax (post-2016), as well as any unpaid building property tax and land value tax. All taxes must be paid within 30 days after signing the contract (step 1).
4. Sellers file the transfer of ownership and pay the stamp duty tax remitted to them by the buyer, plus flat fee (0.1% + 80 NTD). This process usually takes 3 to 5 days.
5. Buyers pay the remaining balance to the seller and complete the transfer.

Given these steps and approximate timeline, we estimate that finalizing an arms-length property transfer takes 38 days, at maximum.[7]

The two distinguishing features of Taiwan's TTS reform are the high tax burden it imposes on sellers, and its focus on very short-term sales. In Table B.1 we catalogue real estate transfer tax policies for the four "Asian Tigers" and top 25 cities by value of investable real estate stock.[8] With the exception of Dallas, Houston, and Phoenix, all of these major markets have either a transfer tax or a capital gains or value-added tax which applies to real estate sales. Outside of Taiwan four markets impose a tax where the rates depend on the holding period

[7]The Sinyi Research Center for Real Estate, estimates an average time on the market of 69 days for Taipei, 55 days for New Taipei, 59 days for Taoyuan, 64 days for Hsinchu, 66 days for Taichung, and 77 days for Kaohsiung. Hence, for a transaction where the buyer is not predetermined, selling a property within four to five months from listing to closing is feasible.

[8]We use the ranking of cities provided by commercial real estate investment firm CBRE in their 2017 report available here. CBRE applies a rule of thumb in the real estate investment industry to value investable real estate stock, which assumes the real estate capital stock is roughly equal to 45% of output once the economy achieves some threshold level of per capita GDP of roughly 27,000 USD.

of the seller, and for the two cities in Japan this preference for long-term investing comes through the capital gains tax system rather than through a transfer tax.[9]

The other takeaway from Table B.1 is that among economies which impose a flat-rate transfer tax, the rates tend to be fairly low, ranging from 0.055% in San Diego to 11% for luxury properties in Madrid. In Taiwan, the transfer tax surcharge we study here is levied on top of two other taxes, the land value increment tax and house transfer income tax, which can easily amount to a rate of 10% paid by the seller for high-value properties.[10] Stamp tax duty schedules in HK and SG are complicated and vary by holding period, sale prices, and non-residency status. These schedules have been continuously reformed over the last decade, and now feature rates as high as 16-20% for non-residents in the top brackets. Yet, since neither HK nor SG impose capital gains tax on income from property sales, effective rates paid by sellers are comparable to those for a flipper in Taiwan once all other transfer tax bases are included.[11]

C Quality-Adjusted Pricing Dynamics

This appendix describes our methods for producing quality-adjusted prices, including the price indices displayed in Figure 1. Residualizing on property characteristics, we show almost complete pass through of the tax on the second home market to sales of previously owner-occupied properties.

As discussed in Section 3.2, we create transaction price indices using newly compiled sales records from local land offices prior to 2012Q3, which we then append to the files available from the government for 2012Q3 to 2019Q4. We also use the underlying pricing model to conduct pre-trend tests in Figure 4, where we allow for time-varying effects of property amenities. We describe the index construction methodology in this appendix. The public records offer a rich dataset of property characteristics for sales involving a combination of

[9]Using the CBRE method applied in Table B.1 we obtain an estimate of $253,973 million USD for investable real estate stock in Taiwan, or about the same as the 10th largest market (Houston). We total the transaction value of all purchases made in 2017 and obtain a value of $111,425 million USD. These two numbers imply annual property turnover equivalent to 44% of Taiwan's entire housing stock.

[10]If behavioral responses to transfer taxes are non-linear in the tax rate, this rationalizes why we find such large effects on trading volume relative to other studies, such as Kopczuk & Munroe (2015) on the 1% "mansion tax" in New York and New Jersey, and Slemrod, Weber, & Shan (2017) on a 0.8 p.p. rate increase in Washington, D.C.

[11]SG and HK have foreign homebuyer stamp duty tax surcharges. SG has a progressive stamp duty tax schedule for buyers (1-4% for domestic buyers) and a progressive set of schedules for sellers which depends on the holding period (higher tax on short-term) and the original purchase date. Deng, Tu, & Zhang (2019) study rate changes at holding period discontinuities in the SG context, and uncover clear lock-in effects and argue sellers who persist in spite of the tax charge a premium.

Table B.1. Key Features of Transfer Taxes in Major Real Estate Markets

	RE stock value	Transfer tax	Capital gains tax (CGT)	Rate(s)	Holding period notch(es)	Exemptions	Legal Incidence
Taiwan	253,973	Yes	Yes	10-15% (flat)	Yes (both)	Inheritance/public entity	Seller
Hong Kong	196,706	Yes	No	1.5-20% (progressive)	✓(buyer surcharge)	N/A	Seller & buyer surcharge
Singapore	217,042	Yes	No	0.33-16% (progressive)	✓(seller stamp tax)	Certain uses (e.g. childcare center)	Buyer & seller (separate rates)
South Korea	758,376	Yes	No	4.6% (flat)	No	N/A	Buyer
Tokyo	711,255	Yes	Yes	3% (flat)	Yes (CGT)	Inheritance	Buyer
New York	656,903	Yes	No	1-2.625% (flat)	No	Sales by public agency	Seller (buyer if seller exempt)
Los Angeles	482,065	Yes	No	0.45% (flat)	No	Court order/collateral/gifts	Seller
Paris	342,389	Yes	No	0.71-6.41% (flat)	No	N/A	Seller
London	333,683	Yes	Yes	2-12% (progressive)	No	New homeowner/value < 125k GBP	Buyer
San Francisco	307,076	Yes	No	0.5-2.5% (flat)	No	Gifts/inheritance/refinancing/trusts	Buyer
Chicago	299,593	Yes	No	1.05% (flat)	No	Collateral/public/divorce	70-30 buyer-seller split
Seoul	290,695	Yes	No	0.02-5% (flat)	No	N/A	Buyer
Osaka	287,726	Yes	Yes	3% (flat)	Yes (CGT)	Inheritance	Buyer
Houston	254,515	No	No	N/A	N/A	N/A	N/A
Washington, D.C.	239,336	Yes	No	1.1-1.45% (flat)	No	Public/gifts/collateral/inheritance/non-profits	Seller
Boston	165,320	Yes	No	0.456% (flat)	No	Gifts/public/value < 2 mil. USD	Seller
Dallas	164,475	No	No	N/A	N/A	N/A	N/A
Atlanta	142,551	Yes	No	0.1% (flat)	No	Court order/divorce/inheritance/firm-to-firm	Seller
Miami	140,244	Yes	No	0.7% (flat)	No	Divorce/inheritance/trusts	Seller
Toronto	130,279	Yes	No	0.5-2.5% (progressive)	No	Public/nursing homes/hospitals/schools	Buyer
Philadelphia	128,534	Yes	No	4.28% (flat)	No	Gifts between family	50-50 buyer-seller split
Seattle	125,147	Yes	No	1.28% (flat)	No	Gifts/refinancing	Seller
Minneapolis	114,309	Yes	No	0.34% (flat)	No	Public/inheritance/refinancing/divorce	Seller
Sydney	113,395	Yes	No	1.25-5.5% (progressive)	No	Inheritance/spouse	Buyer
Detroit	107,711	Yes	No	0.11-0.75% (flat)	No	Gifts/inheritance/energy storage	Seller
Madrid	107,007	Yes	Yes (VAT)	6-11% (flat)	No	Transfer of ownership shares	Buyer
Phoenix	102,956	No	No	N/A	N/A	N/A	N/A
San Diego	99,343	Yes	No	0.055% (flat)	No	Collateral/public/share transfer	Seller
Milan	97,492	No	Yes (VAT)	N/A (10% VAT)	No	Residential/share transfers (VAT)	Buyer

Notes: The table summarizes the provisions of real estate transfer tax and real estate capital gains tax policies in place among the top 25 cities by investable real estate stock (in millions of USD), plus the four "Asian Tigers:" Taiwan, Hong Kong, Singapore, and South Korea. We use the methods outlined by CBRE (2017) to compute real estate stock in a way that allows direct comparison across markets. We note whether the transfer tax charges a flat rate based on the value and other features of the property, or whether the tax rate rises progressively with sale value. Although Taiwan has several taxes incurred by a real estate transaction, for simplicity here we only list provisions of the transfer tax surcharge. We also list common cases in which a transfer would be tax exempt, such as transfers related to posting collateral, divorce, or inheritance. Information on tax policy sourced from various official government websites and research reports from real estate investment firms.

land parcels and or buildings.[12] Our dataset contains information on the number of floors in the unit and building, floor space, land area, land use/zoning, building materials, front-facing road width, location on the street, construction date, and variables generated from remarks enumerated in the public sale record which we use to identify arms-length transactions.

Yet, while addresses are known up to the block level, one challenge is that unique property identifiers are not included, meaning we cannot directly track sales of the same property over time. This not necessarily an issue for hedonic indexing methods, which use a set of potentially time-varying observables to price properties in the cross-section. An hedonic approach would, however, require us to make strong assumptions about the underlying functional form for transaction values given the relatively small set of variables available over the full time period (2000Q1 to 2019Q4) and for all properties.

Therefore, we adopt a hybrid repeat sales/hedonic approach in the spirit of McMillen (2012) and Fang et al. (2015) that transforms the time fixed effects in the following regression to estimate a transaction price index:

$$\log P^c_{i,t} = \delta^c_t + \gamma^c_{\tilde{i}} + \beta^{c\prime} \cdot \mathbf{X^c_{i,t}} + \epsilon^c_{i,t} \tag{C.1}$$

$$P^c_t = \exp(\delta^c_t) \tag{C.2}$$

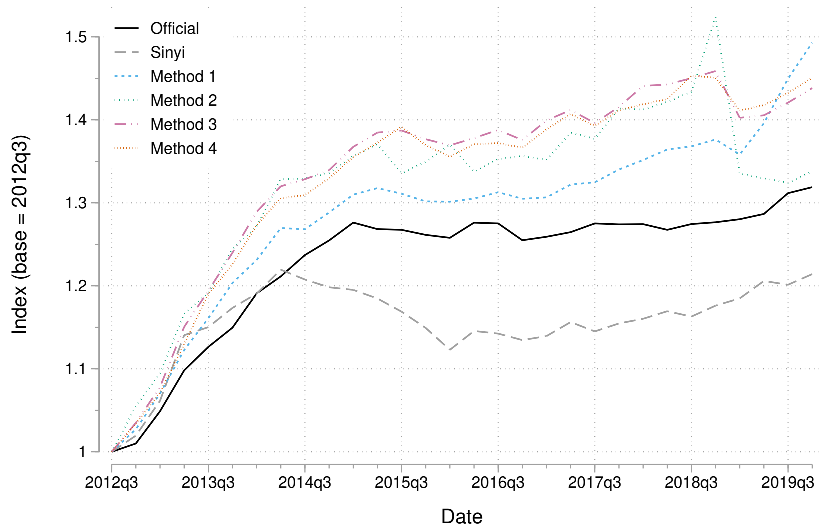
where i indexes a property, t denotes a quarter-year or month-year period, and c refers to a classification based on a combination of the regional market (e.g. Taipei) and property use category (i.e. residential, commercial, industrial). The property type fixed effects $\gamma^c_{\tilde{i}}$ control for all time-invariant observed or unobserved characteristics of the transacted property type.

We make three further restrictions to estimate the model. First, we restrict to transactions involving a single building and drop any transactions with a parking lot or parking space included in the sale. In other words, our sample includes sales of either a land parcel plus structure bundle, or a unit or floor within a building. Second, we drop newly built structures and recently renovated properties. Finally, we identify the $\gamma^c_{\tilde{i}}$ by matching transactions on geolocation information and other features to determine "uniqueness" of a transaction. We consider four variations of this method, with uniqueness defined with increasing stringency as we go down the following list:

1. **Block-level fixed effects:** we assign two transactions the same panel id if they share the same address string (85% of transactions).
2. **Property development fixed effects:** two transactions share a panel id if they have the same latitude and longitude coordinates (18% of transactions).

[12] We exclude from our analysis sales involving parking lot or parking space transfers.

FIGURE C.1. Comparison of Quarterly Housing Price Indices



Notes: The figure compares the official price index, constructed using the public transaction records available from 2012Q3, to the Sinyi Residential Property Price Index, and our indices created using the matching estimator approach. All indices normalized to unity in the base period of 2012Q3. See text for details.

3. **Unique properties up to the nearest 5 m^2 in floor space:** two properties share a panel id if they have the same coordinates and the same building and land area, each rounded to the nearest 5 m^2. This effectively treats two apartments with similar floor space as the same unit, conditional on apartment layout (7% of transactions).
4. **Unique properties up to the nearest 1 m^2 in floor space:** we consider two properties to be the same if they share coordinates and have the same building and land area, each rounded to the nearest 1 m^2. Rounding to the nearest 1 m^2 identifies two units of the same size, accounting for minor typos in the coding of the areas (5% of transactions).

In the regression, the vector $\mathbf{X_{i,t}}$ includes a polynomial in land area and floor space, the number of floors in the building, and the unit floor (for apartments and office space). To the extent that the above methods may assign two distinct but adjacent properties to the same panel id, controlling for $\mathbf{X_{i,t}}$ accounts for small differences due to the height and size which may be relevant to the transaction value.

When we subset to transactions of pre-existing residential structures, our four indices comove strongly with each other and with two other publicly available indices: the official government index and the realty-based Sinyi Residential Property Index. Figure C.1 plots all six indices for the aggregate market over the period 2012Q3 to 2019Q4 when the indices overlap. Notably, the level of the Sinyi index drops below the other indices, including the official index, starting in 2014Q. Since the Sinyi is a hedonic price index, it does not suffer from the positive selection bias on price growth that comes with repeat sales. The official government index is a weighted version of our pricing regression, where the weights are constructed to mitigate the sample selection bias issue inherent in restricting to repeat sales.[13] This upward bias is apparent when we compare how the price level increases with the stringency of our criteria for identifying unique properties.[14]

Despite these differences, the correlation between our index and the official one is 97%, and the correlation between our index and the Sinyi index is 77%. We adopt our Method 1 as our preferred index to maximize the precision of our estimates $\widehat{\delta}_t^c$, maximize sample coverage, and reduce selection bias relative to standard repeat sales. In contrast to popularly referenced indices like the Sinyi, our indices (cf. Figure 1) show a clear price drop of 7% within the quarter after the reform (2011Q2). The main difference between our index and publicly available ones is we include short-term property flips in the estimation sample.

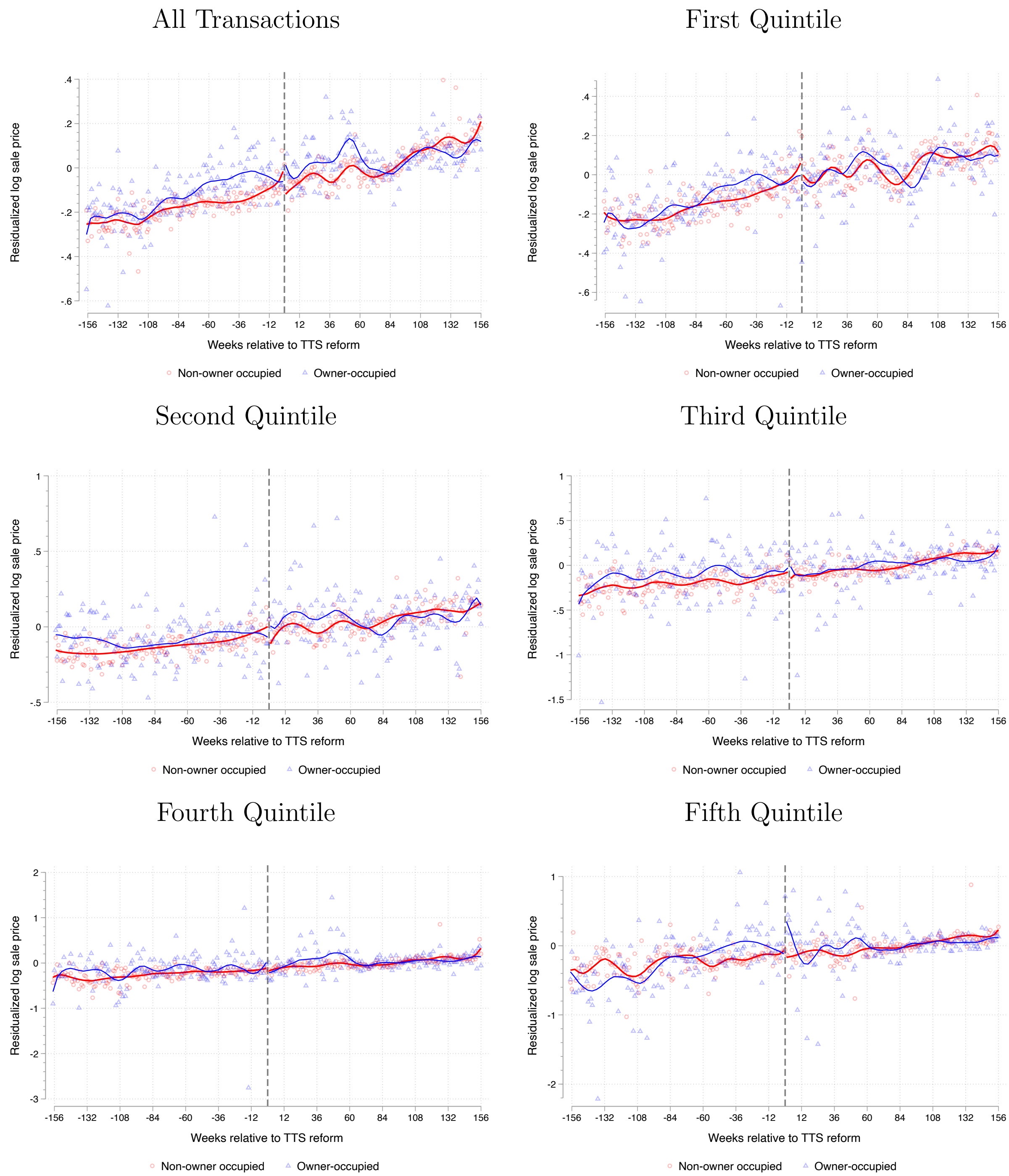
We now use a model akin to the indexing approach in equation (C.1) to examine the behavior of prices in different segments of the housing market around the transfer tax reform. Specifically, we run the regression in (C.1) pooled across cities, where γ_i are block-level fixed effects, and we include a vector of potentially time-varying covariates to adjust for unit characteristics that may vary at the sub-block level. We omit the time fixed effects δ_t, and instead extract the residuals $\widehat{\epsilon}_{i,t}$ and bin those at a weekly frequency.

Figure C.2 displays the results of residualizing prices separately according to the seller's owner-occupied status. In the top left panel where we pool all transactions, we observe a slight jump in prices among sales of previously owner-occupied properties, and prices remain elevated relative to second homes for about a year after the reform. There are a few notable deviations from this general pattern once we divide transactions into quality quintiles based on tax assessed unit values at the *beginning* of the sample. First is that prices for second home sales which are subject to the tax spike by roughly 5% at the bottom of the quality distribution, but are otherwise smooth across the cutoff in other quintiles. Secondly, there is a marked jump of around 10% for prices on sales of owner-occupied homes in the top quintile, reflecting demand spillovers from the reduction in the supply of luxury properties induced by

[13] The official indexing procedures can be summarized by a three-step procedure (translated from this website): (i) Assign properties to the same panel id if they share the same neighborhood designation or are within 500m of each other, the same type and use categories, they were each constructed within 10 years of each other, there is at least six-month gap in transaction dates between the observations. (ii) Price matching houses via automated valuation models (AVM), which are trained on the full set of transactions. These models are then used to create adjusted house prices for the repeat sales according to observables. (iii) Estimate Case-Shiller repeat sales regressions by weighted least squares, where the weights penalize observations according to the length of time elapsed between repeat sales.

[14] Our price levels lie on top of the official ones, in part, because our indices include sales of similar properties occurring within six months. We find in the confidential property records that these extremely short-term sales are very prevalent, particularly in the pre-reform period.

FIGURE C.2. Residualized Sale Prices by Owner-Occupied Status and *ex ante* Price Tier



Notes: Each panel presents the evolution of log sale prices residualized on neighborhood block fixed effects, day of week fixed effects, a quadratic in property age, floor space, land area, unit floor number (for apartments), and number of floors (for single-family homes). In each panel, we separately residualize over the sample of transactions in which the property being sold is currently owner-occupied (blue, triangles) vs. non-owner occupied (red, circles). Sellers only pay transfer tax on sales of non-owner occupied homes. Each point on a graph represents an average residual within a weekly bin. We winsorize prices at the 1st and 99th percentiles before residualizing and binning. Following Gelman & Imbens (2018), we fit local quadratic polynomials to data on either side of the implementation date of June 1, 2011. Quintiles based on tax assessed value per square meter as of the beginning of the sample period.

the new tax. Overall, the dynamics of quality-adjusted prices support the notion of almost complete pass through of the incidence of the tax on second homes to the owner-occupied segment of the housing market.

D Property Flip Tax & Time on Market

We present evidence from listings data that the transfer tax negatively impacted liquidity of investment properties based on time on market (TOM). We obtained residential listings data for the Greater Taipei metro area covering a symmetric one-year period on either side of our reform date of June 1, 2011 from a large, anonymous brokerage firm.[15] The data include basic property characteristics such as the block-level address, last listed price, and floor space and land area. Our sample includes listings removed due to sale *closings*.

We use the address and closing date to merge these listings to the confidential tax returns, which allows us to assess whether the sale was subject to the tax based on owner-occupied status. Since the listing removal date is the contract date (what we observe in the tax data) plus any delays in taking down the listing, merging on the block-level address and listing removal date produces very few exact matches. Hence, we use a two-step procedure to match properties across the listings and tax data:

1. For each property in the listing data, we find the set of properties in the tax records which (i) match on the address and (ii) for which the listing removal date is equal to the contract date $\pm$ 7 days.
2. From the set obtained via step 1, we compute Euclidean distance with respect to the prices and floor space of the sale listing for each potential match and then select the sold property which minimizes that distance.

Applying this procedure we obtain a matched sample with owner-occupier flags and non-missing building characteristics for 4,605 transactions out of a full sample of 17,685 listings closed between June 1, 2010 and June 1, 2012.

Our main bunching results in Section 4.2 support the notion that liquidity declined in the medium-run, as the holding period nearly doubled after the transfer tax, and the missing mass of sales was positive for very long holding periods ($>$ 5 years). The results in this appendix based on TOM suggest that liquidity also declined in the *short-run*. We compare TOM for the pre-reform vs. post-reform period for all transactions and by price tier. Figure

[15] Although we were only able to obtain data covering a short window around the reform, the symmetric nature of this window means seasonality can play only a minimal role in our results.

D.1 shows an average post-reform increase in TOM of 6.9 days in the full set of listings, compared to a difference in means of 6.2 for the matched sample of listings. This indicates that there may be a slight selection bias in our two-step matching procedure which skews towards properties which are more liquid in both the pre-reform and post-reform period. Mirroring the heterogeneity in the high-frequency price analysis of Appendix C, mean TOM increases by 7.5 days in the bottom quintile (p-value = 0.001) and by 9.5 days in the top quintile (p-value = 0.002), but only by 4 to 5 days in the middle of the price distribution.

Figure D.2 indicates that the reduction in short-run liquidity in the housing market was driven by an increase in TOM among the non-owner occupied properties subject to the tax. TOM increased by 7.3 days for non-owner occupied properties (Panel A) but, if anything, declined by a statistically insignificant 4.5 days (p-value = 0.345). Given that 76% of the sales in our matched listings sample are non-owner occupied compared to 75% in the full sample of transactions in the tax data, our matching procedure is not inadvertently selecting on properties which are more or less likely to be subject to the tax on investment homes.

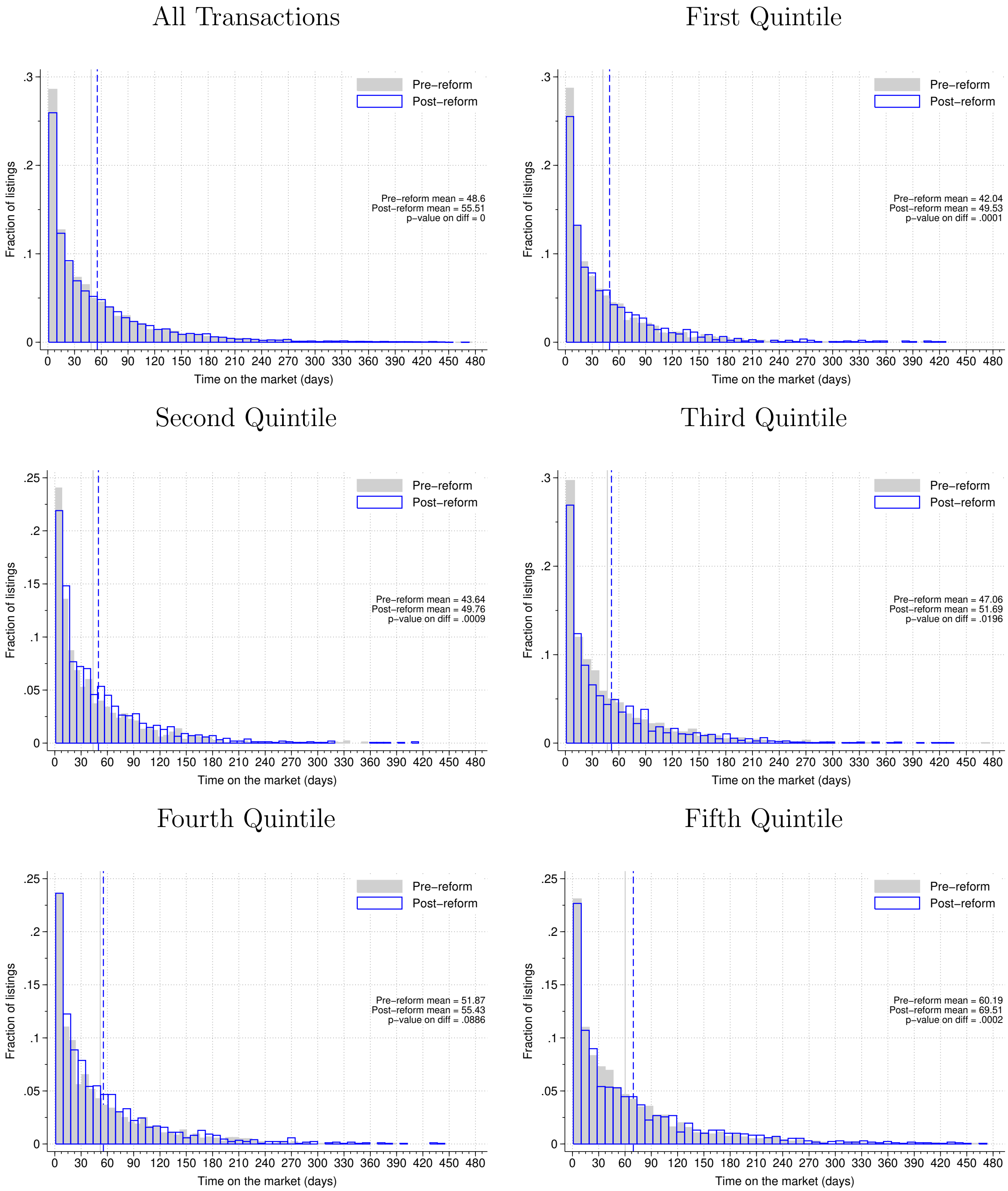
Finally, we adjust the means in Figure D.2 for property covariates and sales seasonality by estimating standard differences-in-differences regressions of the form:

$$TOM_{i,t} = \alpha + \beta_1 \cdot Post_t + \beta_2 \cdot SelfOcc_{i,t} + \beta_3 \cdot Post_t \times SelfOcc_{i,t} + \gamma' \cdot \mathbf{X_{i,t}} + \varepsilon_{i,t} \quad \text{(D.1)}$$

where $TOM_{i,t}$ is time on the market, $Post_t$ is a dummy for the post-reform period, $SelfOcc_{i,t}$ is a dummy for whether the property is owner-occupied, and $\mathbf{X_{i,t}}$ includes covariates such as day-of-week and month-year fixed effects, property age, previous transaction value, land area, floor space, total number of floors, and floor number (for apartments). Our coefficient of interest is the β_3, which captures by how much TOM differed in the post-reform period for the tax-exempt owner-occupied (control) vs. taxable non-owner occupied properties.

The first three columns of Table D.1 show the results from estimating equation (D.1). Average TOM increased by around 7.5 days after the reform, but this increase in TOM was 15 days less for self-occupied properties which were not subject to the tax. The last three columns of Table D.1 replace $SelfOcc_{i,t}$ in equation (D.1) with $Second_{i,t}$, a dummy for whether the listed property was acquired by the seller after their first property. $Second_{i,t}$ is a temporal ordering of homes within the seller's portfolio. Since homes which were acquired later by the seller may still be owner-occupied, and therefore not subject to this tax, the interaction $Post \times Second$ captures the extent to which the tax may have influenced sellers' reservation prices for all but the first property in their portfolio. While we find average TOM for second homes was higher (statistically insignificant) than for first homes, we do not observe any meaningful difference across the tax reform with respect to the temporal

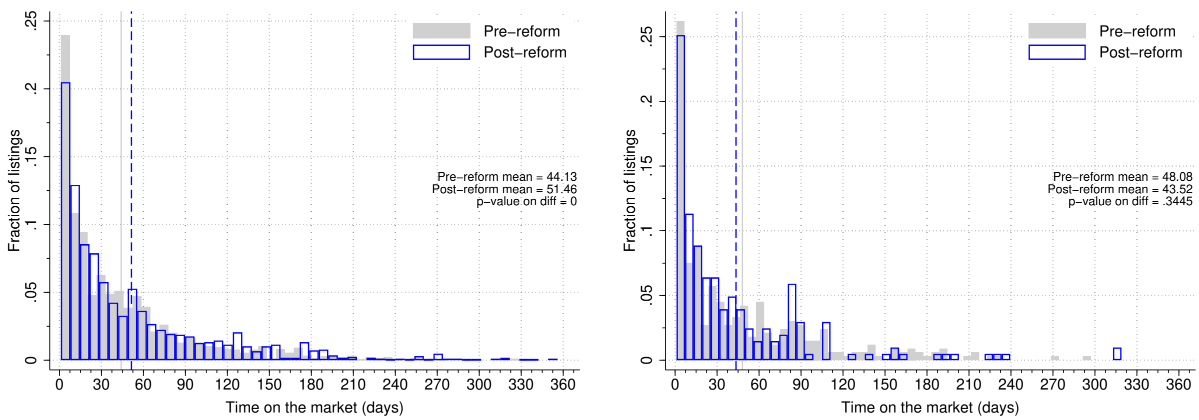
FIGURE D.1. Time on Market by *ex ante* Price Tier



Notes: Each panel compares pre-reform and post-reform residential listings in the greater Taipei metro area by time on market. Data from a large, but anonymous, brokerage firm. We define time on market as the number of days between the initial listing date and the day the listing was removed. Pre-reform includes listings removed within the year prior to the Tobin tax reform, while post-reform includes listings posted and removed within the year after the reform. The first panel pools all transactions, while the remaining five panels divide the transactions into quintiles based on the property's last assessed value. Solid grey vertical lines indicate the mean time on market in the pre-reform period, while blue dashed lines show the mean in the post-reform period.

FIGURE D.2. Time on Market by Occupancy Status

A. Non-Owner Occupied Properties (Taxable) B. Owner-Occupied Properties (Tax-Exempt)



Notes: Each panel compares pre-reform and post-reform residential listings in the greater Taipei metro area by time on market. Data from a large, but anonymous, brokerage firm. We define time on market as the number of days between the initial listing date and the day the listing was removed. Pre-reform includes listings removed within the year prior to the Tobin tax reform, while post-reform includes listings posted and removed within the year after the reform. Panel A includes listings we match to the tax data which are non-owner occupied at the time of sale, while Panel B includes listings which are owner-occupied at the time of sale and therefore not subject to the surcharge. Solid grey vertical lines indicate the mean time on market in the pre-reform period, while blue dashed lines show the mean in the post-reform period.

ordering of home acquisitions. Overall, we conclude it is unlikely that liquidity was negatively impacted in segments of the housing market which were not subject to the flip tax.

E Constructing Weather Shocks

This appendix provides more details on how we compiled the weather data used in Section 5.2. We scrape daily weather readings over 2005-2019 from all 832 stations scattered across Taiwan via the CoDiS Database of the Central Weather Bureau (CWB), and merge in the dates when the CWB issued typhoon warnings from the Typhoon Database. According to the official classification system, typhoon warnings are issued whenever winds are expected to reach a sustained speed of at least 74 mph (118 km/h).[16] Meteorological stations are geographically distributed across Taiwan such that each of the 22 administrative regions contains at least two, with more populated regions being serviced by more non-automated stations due to the increased likelihood of property damage should a severe storm arrive.

There are three types of ground stations which record weather readings:

1. Main stations (N = 32) staffed by government employees who record all weather

[16] cf. World Meteorological Organization Technical Document, Typhoon Committee Operational Manual.

Table D.1. Time on Market and Occupancy Status: DiD Results

	(1)	(2)	(3)	(4)	(5)	(6)
Post	7.59***	7.39***	7.52***	7.71**	6.88*	6.92*
	(1.87)	(1.89)	(1.90)	(3.51)	(3.54)	(3.57)
SelfOcc	1.14	2.21	2.31			
	(3.60)	(3.82)	(3.82)			
Post × *SelfOcc*	−15.01***	−14.62***	−14.82***			
	(5.52)	(5.62)	(5.62)			
Second				2.88	2.76	2.70
				(2.39)	(2.38)	(2.38)
Post × *Second*				−2.31	−1.44	−1.36
				(4.06)	(4.10)	(4.11)
District × month-year FEs	✓	✓	✓	✓	✓	✓
Property controls		✓	✓		✓	✓
Day-of-week FEs			✓			✓
N	4,605	4,553	4,553	4,605	4,553	4,553
Adj. R^2	0.021	0.033	0.033	0.019	0.031	0.031

Notes: The table displays regression results from estimating differences-in-differences (DiD) specifications of the form in equation (D.1), with time on market (TOM) in days as the outcome variable. The first three columns include a dummy for whether the listing is for an owner-occupied property ($SelfOcc$), while the last three columns instead include a dummy for whether the listing is for the seller's second (or later) home. We define a "second home" here as one that was acquired after the seller's original home purchase. Property controls include building age, previous transaction value, floor space and land area, the number of floors on the property, or the floor of the unit if it is in an apartment building. Standard errors in parentheses clustered at the property panel id level. $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

variables, including: daily average wind speed, max wind gust, precipitation, sea surface pressure, air pressure, hours of precipitation and sunlight, cloud coverage, visibility, UVI, dew point, humidity, and average and high/low temperature.

2. Automated stations (N = 485) only record crucial typhoon forecasting variables, including variables related to temperature, station pressure, humidity, wind speed, and accumulated precipitation.
3. Precipitation stations (N = 315) only report accumulated precipitation. Stations in this category are also equipped to provide automated readings.

For each station and each day, we take averages and maxima/minima over hourly readings. Even if a station is equipped to report certain weather variables there can be missing values due to equipment damages or malfunctions, both of which are more likely to occur during severe weather events. Therefore in our analysis we focus on either the manned stations in the first category or a balanced panel of stations within the first two categories.

Table E.1. Summary Statistics for Key Meteorological Station Readings

	Taipei/New Taipei		Other Metros	
	Peak season	Non-peak	Peak season	Non-peak
Avg. # typhoon warning days	15.8	3.9	15.8	3.9
Max daily precipitation (in)	17.5	16.7	37.8	26.7
Cumulative precipitation (in)	38.9	82.4	47.0	48.9
Avg. wind speed (mph)	3.9	4.0	3.8	4.3
Max wind gust (mph)	101.4	88.3	153.9	126.6
Avg. station pressure (hPa)	989.7	997.4	965.4	973.1
Min. station pressure (hPa)	896.5	907.4	627.8	634.0
Avg. daily high temperature (°F)	89.5	73.6	86.3	74.6
Max daily high temperature (°F)	116.6	115.8	112.7	111.5
N	19,944	64,440	74,790	241,650
# Stations	36	36	135	135

Notes: Observations from a balanced panel of stations reporting typhoon forecasting variables in the pre-reform period. Peak season refers to daily weather readings during July, August, and September, while non-peak includes all other months. Typhoon warnings are set at the national level, and a full history of announcements going back to 1960 is available from the Central Weather Bureau Typhoon Database.

In unreported property-level results, we match each property sale in our dataset to the nearest station – according to Haversine distance – as of the transaction date. The average property in our sample is located within 10.2 km of one of the first two types of weather stations (median of 7.4 km). To account for the fact that readings may be a less precise measure of local storm severity in rural areas where CBDs are further from stations, we also confirmed robustness of property-level specifications to including polynomial functions of distance to the nearest station. Echoing our results for aggregate volumes, we find that typhoon-level rainfall events result in a 0.002% lower probability that a second home sells on that date, and that this negative effect on sales probability persists for several weeks.

Table E.1 provides summary statistics for the key weather variables which are related to forecasting Pacific storm severity. To create a consistent sample across variables, we exclude the 40% of stations which only report automated precipitation readings and create a balanced panel of the remaining stations. Taiwan averages 16 days with active typhoon warnings during the peak season but only four days during non-peak months. Maximum daily precipitation across all stations is 5% higher during typhoon season in the Taipei-New Taipei area, and 42% higher across stations in all other metro areas. The other key metrics which accompany storms are also more pronounced during the peak season and outside the Taipei area: low station pressure readings and high maximum wind gusts.

Are precipitation and wind speed sufficient to characterize the severity of weather

Table E.2. Factor Loadings for Key Weather Variables

	Factor 1 *"Fair weather"*	Factor 2 *"Low pressure"*	Factor 3 *"High wind"*	Factor 4 *"Heavy rainfall"*
Avg. station pressure	0.37	−0.38	0.01	0.21
Max station pressure	0.37	−0.38	0.02	0.21
Min station pressure	0.37	−0.37	0.01	0.21
Avg. temperature	0.33	0.43	−0.01	0.19
Max temperature	0.33	0.44	−0.04	0.08
Min temperature	0.31	0.42	0.00	0.28
Avg. relative humidity	−0.34	0.04	−0.32	0.38
Min relative humidity	−0.33	−0.07	−0.19	0.46
Avg. wind speed	−0.13	−0.01	0.65	0.14
Max wind gust	−0.13	0.06	0.66	0.17
Cumulative precipitation	−0.14	0.02	0.00	0.58

Notes: The table reports the factor loadings for each variable recorded by the main and automated weather stations in our sample. We restrict attention to the four factors (columns) with eigenvalues greater than one.

conditions? We test the validity of our interpretation of the meteorological data by using factor analysis to identify the four factors with eigenvalues above one, which together capture 88% of variation in weather patterns. Table E.2 reports the factor loadings for the eleven variables which are common to all main stations and automated stations in our sample. The first factor loads on fair weather characteristics: high atmospheric pressure, high temperature, low humidity, limited wind and precipitation. The second loads negatively on pressure and positively on temperatures. Since, these two characteristics precede tropical storm systems, this factor identifies a storm forecast component. The third factor loads prominently on average and maximum wind speed, while the fourth factor loads on humidity and accumulated rainfall. Hence, we loosely interpret Factor 1 as a fair weather factor, Factor 2 as a low pressure system, Factor 3 as high wind, and Factor 4 as heavy rainfall.[17]

In Table E.3 we replace the $Weather$ shocks in our baseline volume regression (5.2) with the four factors identified in Table E.2. Consistent with our interpretation, the four factors have the expected sign on property sales. Fair weather is positively associated with volume, while wind and rain are negatively associated with volume. There is no obvious economic reason why low atmospheric pressure conditional on other weather conditions would influence selling behavior, and consequently the association of this factor with volume is statistically insignificant. When we run a regression with all four factors in column 6, the wind factor is

[17]We obtain similar results when we restrict to main stations, which offer a larger set of meteorological variables, including visibility, sunshine, cloud coverage, dew point, and duration of rain vs. sunshine. The main difference is we identify a fifth factor with an eigenvalue greater than one, which we interpret as an "overcast" factor, and which also loads negatively on sales volume.

Table E.3. Principal Weather Factors and Real Estate Sales

	(1)	(2)	(3)	(4)	(5)	(6)
$Factor1 \times Summer$	17.54***					6.35
"Fair weather"	(3.34)					(6.69)
$Factor2 \times Summer$		−4.46				5.63
"Low pressure"		(6.90)				(7.27)
$Factor3 \times Summer$			−17.67***		−13.66***	−14.29***
"High wind"			(2.89)		(2.74)	(2.93)
$Factor4 \times Summer$				−13.24***	−8.02***	−3.42
"Heavy rainfall"				(2.60)	(2.32)	(5.00)
7-day FEs	✓	✓	✓	✓	✓	✓
Day-of-week FEs	✓	✓	✓	✓	✓	✓
Damages Controls	✓	✓	✓	✓	✓	✓
N	4,681	4,681	4,681	4,681	4,681	4,681

Notes: The table presents results from estimating time series regressions according to equation (5.2) using the principal components from Table E.2 instead of the usual rainfall and maximum wind speed shocks. The outcome variable in each column is 100 times the deviation of aggregate log sales volume from its 6-month symmetric moving average. We include daily observations over the period 2006-2016, which encompasses a full El Niño cycle. All regressions control for daily counts of casualties and properties lost due to flooding and typhoons. Newey-West standard errors with eight lags in parentheses adjust for serial correlation and heteroskedasticity. We select the minimum possible lag order such that the estimator for the covariance matrix is consistent. $***p < 0.01, **p < 0.05, *p < 0.1$.

the only one with an effect on volume. This suggests what we interpret as a rainfall effect on noise trading in our main results may in fact be due to wind once we condition on a richer set of atmospheric conditions. However, wind is not a substitute for rain, as both factors have a significantly negative effect on volume (column 5).

Strong storms may entail property damage which alter sales volume by either lowering the quality of the available housing stock or inducing owners to engage in costly and time-consuming renovations. We downloaded official statistics from the National Fire Agency going back to 1960 on reported fatalities, injuries, full and partial property losses, and disaster crews and equipment deployed. This information is itemized by the date and type of disaster, allowing us to match the damages to the typhoon warnings and other weather variables in our dataset. Over our pre-reform window of 2005-2011, the average flood or typhoon event during the regular typhoon season generated 70 casualties (mostly minor injuries), completely destroyed 20 houses, and partially destroyed eight houses. Overall, the typical severe weather event was not a substantial shock to the quality of investable real estate. Nevertheless, we control for storm-induced damages in all weather specifications presented in Section 5.2.

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