Heterogeneous Passthrough from TFP to Wages*

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Abstract

We examine the transmission of firms' idiosyncratic productivity shocks to workers' wages using matched employer-employee data from Denmark. Our novel method controls for productivity differences across firms due to unobserved differences in labor quality and for workers' endogenous job mobility decisions. We find an average elasticity of workers' hourly wages to firms' productivity of 0.08. This implies that a productivity shock of one standard deviation generates a change of $1,100 US dollars in annual wages for the average worker in Denmark. The passthrough of firm shocks to wages is strongly asymmetric, in that workers' wages are twice as responsive to negative shocks as positive shocks. Failing to control for endogenous worker mobility dramatically underestimates the passthrough of negative shocks and reverses the direction of asymmetry. Our results also indicate significant heterogeneity across firm and worker characteristics. We show that a simple model where firms with labor market power interact strategically can rationalize our findings. Through the lens of this model, our estimates imply an average firm-level labor supply elasticity of 5.7 and average wage markdowns of 15%.

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1 Introduction

How do fluctuations in firms' idiosyncratic productivity affect workers' wages? How and why does this vary over time and across firms and workers with different characteristics? The answers to these questions are important for our understanding of how employers differ in their ability to set wages, the role of firms' shocks in determining workers' income instability, and why workers with similar characteristics receive different salaries across firms.

In this paper, we use administrative matched employer-employee panel data covering the entire private sector of Denmark to provide new evidence on the elasticity of workers' hourly wages with respect to firms' productivity shocks. We refer to this elasticity as "passthrough". The richness of our data set allows us to address two challenges faced by the existing literature. The first is to identify unexpected shocks to firms' productivity. Most papers in the literature proxy for these shocks using fluctuations in value-added, sales, or revenues, all of which are themselves endogenous functions of wages and employment and thus imperfect measures of exogenous or unexpected firm productivity shocks. We instead leverage the firm- and worker-level information available in our data set to estimate total factor productivity (TFP) at the firm level while controlling for the endogeneity of inputs using a dynamic structural model of the firm.

Our TFP estimation procedure builds on the non-parametric methods proposed by Gandhi, Navarro and Rivers (2020)—hereafter GNR—which we complement by using worker-level data to control for differences in the quality of labor employed by firms. Specifically, each firm's labor input is calculated as the contribution of its workers' observed and unobserved characteristics to hourly wages estimated from a series of two-way fixed effect regressions, as in Abowd, Kramarz and Margolis (1999)—hereafter AKM. We deviate from the standard AKM wage model by estimating time-varying firm effects which allow changes in firms' characteristics and productivity to have a dynamic impact on workers' wages.

The second challenge derives from workers' endogenous job mobility choices. In general, the literature has focused on incumbent workers who remain at the firm in consecutive periods (stayers). This approach will lead to biased estimates of passthrough if workers switch jobs in response to a decrease in firm productivity. To address this second challenge, we control for workers' endogenous mobility by exploiting independent variation derived from workers' household linkages. In particular, we estimate workers' probability of staying at a firm as a function of their own and their employer's characteristics, as well as their marital status, the observable characteristics of their spouse, and the characteristics of the spouse's employer. The underlying assumption is these observables will affect worker's job mobility decisions, but not the elasticity of wages to productivity in their own firm. We also directly examine how the productivities of a transitioning worker's origin and destination firms affect their wages.

Our main empirical analysis consists of a series of worker-level panel regressions that relate log hourly wage growth for stayers with different measures of shocks to firm productivity. Our estimates allow us to reach three main results. First, there is significant passthrough from firms' idiosyncratic productivity shocks to workers' wages. We find a passthrough elasticity of hourly wages to changes in overall TFP of 0.08, which is economically and statistically significant. This implies that a full-time worker employed at a firm that experiences a one standard deviation change in TFP, receives change in annual earnings of $1,075 in US dollars, or around 1.8% of the average annual salary in Denmark. These wage changes are long lasting, with passthrough from persistent TFP shocks remaining undiminished 4 years after the shock. Considering that in a typical year around 20% of the firms in our sample (which employ around 25% of all private-sector workers in Denmark) experience a change in the productivity of at least one standard deviation from the mean, we conclude that fluctuations in firm productivity have important implications for labor earnings inequality and instability.

Second, we find that the passthrough is asymmetric in that the elasticity of workers' wages to a negative change in productivity is almost twice as large as the elasticity to a positive change in productivity. We refer to this relationship as "negative asymmetry" in passthrough, as opposed to "positive asymmetry" which would imply that wages are more responsive to positive than to negative shocks. Quantitatively, an increase in productivity of one standard deviation generates an average increase in annual earnings of $840, whereas a decrease in productivity of the same magnitude generates a drop in annual earnings of $1,580.

Third, our results indicate that accounting for workers' endogenous mobility plays an important role in shaping the impact of firms' shocks on workers' wages. In particular, selection biases the passthrough coefficient toward zero for both positive and negative shocks, reducing the overall impact of the productivity shocks on wages. The bias is much more important for negative than for positive shocks. In fact, if we were to ignore workers' mobility, we would conclude that there is significant downward wage rigidity, and the wage elasticity to positive shocks is almost twice the elasticity to negative shocks, which is the opposite of what we find in our baseline selection-corrected results.

Exploring the heterogeneity of the passthrough, we find that it varies considerably across workers' characteristics, firms' characteristics, and over the business cycle. On the firm side, we find lower passthrough among large, high productivity, and high market share firms relative to small and low productivity firms. On the worker side, we find that high-income workers have a higher passthrough from negative shocks than low-income workers. Similarly, we find that the wages for older and long-tenured workers increase more after a positive productivity shock and decline less after a negative shock than for young and recently hired workers. Finally, we find that during recessions, the passthrough from positive productivity shocks collapses—becoming essentially zero—whereas the passthrough from negative shocks remains almost unaltered. In other words, we find that during recessions, workers' wages become unresponsive to positive (but not negative) shocks to firms' productivity.

These results are difficult to reconcile with a canonical model where labor markets are perfectly competitive and individual firms have no role in setting wages. To interpret our results, we consider a simple model of an imperfect labor market which nests several possible mechanisms that can generate passthrough from firm shocks to wages, such as adjustment costs, job amenities, and labor market power. We start with a general framework to show that in a model where firms face an upward-sloping labor supply curve, there is positive passthrough. This general framework also predicts the selection bias we find in the data. However, a monopsonistic version of this model in which firms are atomistic is inconsistent with the asymmetry and heterogeneity we observe in the data. Instead, a model in which firms interact strategically and have some labor market power is more consistent with our empirical results. Under general conditions this model implies larger passthrough from negative shocks than for positive shocks and a passthrough which is declining in firm size, productivity, and market power—which is in line with our empirical estimation results.

We then shift our focus to workers that switch firms between periods. As implied by the model and the selection issue discussed above, we find that negative firm productivity shocks dramatically increase a worker's probability of leaving a firm and switching to another employer, while positive productivity shocks have little effect on outward worker mobility. Consistent with standard job-ladder models, we find that workers who move from low- to high-productivity firms experience a significant increase in hourly wages, with larger gains associated with greater jumps in the firm productivity distribution. Quantitatively, workers who experience 10 log point increases in hourly wage have moved to firms with 18 log point higher productivity than their previous employer. A 50 log point wage gain, on the other hand, is associated with a move to a 47 log point more productive firm on average. Interestingly, workers with larger wage gains are not moving into firms with higher productivity than workers with smaller wage gains, but rather moving out of firms with lower productivity. For example, if we compare workers gaining 50 log points in wages to those gaining 10 log points, both are moving into firms with roughly the same productivity, but the former are moving out of firms with 25 log points lower productivity than the latter. Notably, the average switcher in every percentile of the wage growth distribution is moving from a firm with shrinking productivity to a firm with growing productivity, suggesting that even workers who move down the job ladder are moving to firms with higher productivity growth rates.

In the last section of the paper, we apply the insights gained from our theoretical framework to our estimates of the passthrough elasticity in order to back out the implied labor supply elasticity. We estimate an average labor supply elasticity of 5.66, which suggests that the average wage markdown is around 15% below marginal productivity and that firms in these labor markets enjoy significant market power.

Related Literature. Our paper relates to the rent-sharing literature that studies the relationship between firm shocks and worker earnings. Guiso, Pistaferri and Schivardi (2005) study the passthrough from firms' value-added shocks to wages and the degree of insurance provided by firms using matched employee-employer data from Italy. They find a passthrough coefficient of 0.07 from permanent shocks and almost no passthrough from transitory shocks to firms. Their methodology has been implemented for several countries, including the United States, delivering surprisingly similar results.[1]

We differentiate from Guiso *et al.* (2005), and the subsequent literature, in at least three important ways. First, we carefully measure productivity shocks and control for worker quality using a dynamic structural model of firm production. Second, by using hourly wages, we are able to isolate the impact of firm shocks on wages separately from the impact on hours. Third, we control

[1] Several other recent papers study the empirical and theoretical relation between firm's shocks and worker's wages. See for instance, Berger *et al.* (2019), Friedrich *et al.* (2019), Carlsson *et al.* (2015), Garin *et al.* (2018), Guertzgen (2014), Lamadon *et al.* (2017), Ai and Bhandari (2018), Rute Cardoso and Portela (2009), Barth, Bryson, Davis and Freeman (2016), Lamadon (2016), Juhn, McCue, Monti and Pierce (2018), Balke and Lamadon (2020), Maibom and Vejlin (2021), among others. See Manning (2011), Manning (2020), Card *et al.* (2018), and Guiso and Pistaferri (2020) for recent surveys.

for the endogenous selection of workers in response to firm shocks and directly estimate passthrough for both incumbent and transitioning workers. We find an average passthrough coefficient that is in line with other estimates in the literature. Our findings of significant asymmetry and heterogeneity in passthrough, however, are novel.

More recently, several authors have used quasi-experiments to identify shocks to firms and how these are passed on workers' wages. For instance, Kline *et al.* (2019) study rent sharing among innovative firms that receive patent approvals. Similarly, Howell and Brown (2020) use cash windfalls received by firms from government grants as a measure of shocks. These papers focus on a very particular, yet important, set of young and small firms, but might not be representative of the entire economy. Furthermore, the quasi-experimental approach only allows them to study positive shocks to firms, which we find to generate much less passthrough than negative shocks. Our methodology, in contrast, allows us to estimate the passthrough for both positive and negative shocks across the entire private sector.

Our productivity estimation approach is similar to those proposed by Hellerstein and Neumark (2007), Fox and Smeets (2011), and more recently, Bagger, Christensen and Mortensen (2014) and Bagger and Lentz (2019), who also incorporate worker-level characteristics to control for differences in the labor quality across firms. In particular, Bagger *et al.* (2014) incorporate firm-time fixed effects into an AKM-style wage model, as we do here. We differ from their paper in that our TFP estimation procedure is more flexible and allows the identification of transitory and persistent shocks to firms' productivity. Lochner and Schulz (2020) also merge the AKM approach to measuring labor quality with a production function estimation method similar to what we use in this paper. We differentiate from their study in that we consider a richer set of workers' characteristics in our AKM estimation and in that we allow for the firm effect to vary with time.

Our work also contributes to the recent literature on estimating labor market power. For example, our estimates of the labor supply elasticity and wage markdowns in Denmark are remarkably similar to recent estimates for the United States by Azar *et al.* (2019), despite their use of completely different methods and data. We also provide a theoretical link between market power and passthrough.

The rest of the paper proceeds as follows. In Section 2 we derive and discuss the passthrough from TFP shocks to wages in a simple model of labor market power. In Section 3, we introduce our data sources and discuss our sample selection and in Section 4 we present our estimation strategy.

Section 5 discusses our baseline results. Section 6 studies how the passthrough from firms' shocks to workers' wages varies across firms and workers with different characteristics, whereas Section 7 studies how switching between firms with different productivity levels affects wages. Finally, Section 8 discusses the implications of our estimates for the labor supply elasticity. Section 9 concludes.

2 Simple Model of Passthrough

In order to build intuition for our empirical findings, we begin by presenting a simple model of imperfect labor markets and discuss its implications for the direction and heterogeneity in passthrough from productivity shocks to wages. A model of imperfect markets is a natural starting point since passthrough will necessarily be zero in a model with perfectly competitive labor markets where there is a single market price for labor and atomistic firms play no role in setting individual wages. We begin with a general model of an imperfect labor market where firms face a general upward-sloping labor supply curve. We then present a micro-founded parameterization of this simple model which nests several possible mechanisms which generate passthrough, including adjustment costs, work place amenities, and market power.[2]

2.1 A Simple Model of Labor Demand

Consider a profit-maximizing firm with production function $Y = Af(L)$, where $A > 0$ is the firm's idiosyncratic productivity and the production function is such that $f(L) > 0$, $f' > 0$, and $f'' < 0$. The firm faces a labor supply curve given by $L^s = g(W)$, where $W > 0$ is the real wage per unit of labor, and $g(W)$ is twice continuously differentiable with $g(W) > 0$ and $g' > 0$. Theorem 1 shows that under very general conditions, an increase in A generates an increase in W, that is, there is positive passthrough from firms' shocks to wages.

Theorem 1. *Under the preceding assumptions on A, W, f, and g, the elasticity of workers' wages with respect to firms' productivity shocks is positive, $\frac{dW}{dA}\frac{A}{W} > 0$, if either of the following two conditions holds: (a) $g'' \leq 0$, or (b) $g'' > 0$ and $d\phi(W)/dW > 0$ with $\phi(W) \equiv g(W)/g'(W)$.*

Proof. See appendix E. □

The intuition behind this result is that when a firm experiences an increase in productivity,

[2] In Appendix F, we discuss other models where passthrough arises from financial constraints or search frictions.

A, the optimal quantity of labor demanded by the firm increases. In order to attain a higher level of employment, the firm must move up the labor supply curve by increasing the wage paid to its workers. Any non-constant labor supply curve will thus imply some degree of passthrough. Theorem 1 indicates that the passthrough elasticity will be *positive* on any part of the labor supply curve that is *increasing* and not *too convex* in wages.[3] A corollary of this theorem is that as long as the labor supply curve is not log-linear in wages (i.e., as long as it does not take the form $L^s = Bw^\theta$ for some $B > 0$ and $\theta > 0$), the passthrough elasticity will be a function of the wage, and thus also a function of anything that affects wages such as productivity or market power. This corollary has two direct implications for passthrough, both of which we examine in our empirical section below. First, a dependence on wages will drive heterogeneity in passthrough across firms with differing levels of productivity, amenities, market power, and so on. Second, dependence on the wage level will also drive asymmetry in passthrough: *positive* productivity shocks will generate larger (or smaller) percentage changes in wages than *negative* productivity shocks of the same magnitude.

A Micro-founded Model of Labor Market Power

The previous case is a general starting point that suggests a link between firms' shocks and workers' productivity. To gain further intuition, we consider a general micro-founded model similar to Manning (2020) and Berger *et al.* (2019). Assume that a labor market is populated by N workers and a set $\mathcal{J}$of J firms. Each firm operates a simple revenue production function $Y_j = A_j L_j^\alpha$ where A_j represents a firm-specific revenue shifter (such as a productivity or demand shock), and α determines returns to scale.[4] We assume that the firm operates with decreasing returns to scale, such that $\alpha \in (0, 1)$.

Workers can choose to work for any firm $j \in \mathcal{J}$ or choose non-employment, denoted by 0. Working for firm j provides utility $V_{ij} = \theta \log W_j + \log B_j + \eta_{ij}$ where W_j is the wage paid to workers at firm j, B_j is an exogenous non-pecuniary benefit provided to all workers at the firm, and η_{ij} is the (unobserved to the firm) individual utility gained by worker i at firm j.[5] We also

[3]Another way to write the last condition is that $\frac{\partial \epsilon_W^L}{\partial W}\frac{W}{L} < 1$, where ϵ_W^L is the labor supply elasticity. So passthrough is positive as long as the labor supply elasticity is positive and not itself elastic in wages. Note that the conditions in the theorem are actually stronger than they need to be, since ϵ_A^w will be positive for $\phi'(W) < 0$ as long as $\frac{2\left(g'(W)\right)^2 - g(W)g''(W)}{((Wg'(W)+g(W))g'(W))} > \frac{f''(g(W))g'(W)}{f'(g(W))}$.

[4]We abstract from capital for simplicity, but this production function can be derived from a more general production function of the form $Y = A(K^{1-\gamma}L^\gamma)^\beta$ where the optimal level of capital has been subsumed into the productivity term and $\alpha \equiv \frac{\gamma\beta}{1-(1-\gamma)\beta} \leq \beta$ (see Berger *et al.* (2019)).

[5]This term can represent any individual characteristic which might affect the employment decision including, individual preferences, changes in family structure, employment outcomes of other family members, etc.. Our empir-

assume that utility is increasing in the (log) wage so that $\theta > 0$. The outside option of non employment provides utility $V_{i0} = \theta \log W_0 + \log B_0 + \eta_{i0}$. Finally, we assume that η_{ij} follows a type 1 extreme value distribution. This provides the following expression for the share of workers at firm j,

$$S_j = \frac{B_j W_j^\theta}{B_0 W_0^\theta + \sum_{k \in \mathcal{J}} B_k W_k^\theta} \tag{1}$$

where the number of workers at firm j is $L_j = S_j N$ and $I \equiv B_0 W_0^\theta + \sum_k B_k W_k^\theta$ represents a market-level wage index. The labor supply elasticity which arises from this model for firm j is $\epsilon_W^L = \theta(1 - S_j)$. As we discuss below, this simple framework nests several key models of labor supply and passthrough.

Log-Linear Labor Supply

Consider first a case in which each firm is atomistic, so that $S_j \approx 0$ and firms take the market wage index I as exogenous. This reduces the labor supply curve to the following log-linear form: $g(W) = \tilde{B}_j W_j^\theta$, where $\tilde{B}_j \equiv \frac{B_j}{I} N$ is an exogenous labor supply shifter and the labor supply elasticity is a constant $\epsilon_W^L = \theta$. This model corresponds to the classical models of atomistic monopsony frequently used in the trade, labor, and macroeconomic literatures. As we suggested earlier, in this case, the passthrough from a change in firms' productivity to workers' wages, $\epsilon_A^w = \frac{dW}{dA} \frac{A}{W}$, is given by $\epsilon_A^w = \frac{1}{1+\theta(1-\alpha)}$ which is positive and constant for all firms and does not depend on firm productivity, firm size, or the wage level.[6] Note that the passthrough from TFP to wages in this model is decreasing in the labor supply elasticity parameter, θ, and increasing in the returns to scale parameter, α. Since the passthrough elasticity does not depend on A_j, this simple model also predicts *symmetric* passthrough from positive and negative productivity shocks to wages. Deviations from this simple log-linear model will tend to generate heterogeneity and asymmetry in passthrough.[7]

Labor Market Power

Asymmetry and heterogeneity in passthrough can also arise from market power and oligopsonistic competition. To see this the case, we return to the general logit demand model above in

ical strategy will use data on these employment-relevant individual characteristics to help identify the passthrough elasticity.

[6] See Appendix E for derivations.

[7] For example, in Appendix E.2.2 we show that adding linear adjustment costs to this basic model with atomistic firms will generate positive asymmetry in passthrough, and a passthrough elasticity which is decreasing in firm size and productivity.

which firms are non-atomistic. This framework allows for strategic interaction between firms with varying degrees of labor market power. Each firm j faces the following labor supply function

$$g(W_j) = \frac{B_j W_j^\theta}{B_0 W_0^\theta + \sum_{k \in \mathcal{J}} B_k W_k^\theta} N = \frac{B_j W_j^\theta}{I} N \tag{2}$$

where the firm interacts strategically with other firms by endogenizing the effect of wage changes on the wage index, I. It is straightforward to show that the passthrough elasticity in this model is a function of the demand and supply parameters, as well as the firm's relative labor share. In particular, the passthrough elasticity, ϵ_A^w, is given by,

$$\epsilon_A^w = \frac{1 + \theta(1 - S_j)}{1 + \theta(1 + (1 + \theta(1 - S_j))(1 - \alpha)(1 - S_j))}, \tag{3}$$

where S_j is a strictly increasing function of productivity, A_j. We know ϵ_A^w is positive since $\alpha \in (0, 1)$, $S_j \in (0, 1)$, and $\theta > 0$.

The passthrough elasticity curve in this setting (as a function of S_j and therefore A_j) is hump-shaped, with a peak determined by the relative elasticity of the labor supply. More precisely, $\frac{d\epsilon_A^w}{d \log A} > 0$ if and only if $0 < \alpha < \frac{\theta}{1+\theta}$ and $0 < S_j < 1 + \frac{1}{\theta} - \sqrt{\frac{1+\theta}{(1-\alpha)\theta^2}}$. This means that in a labor market where $\alpha < \frac{\theta}{1+\theta}$, there will be a size cutoff S^* such that passthrough is negative asymmetric and decreasing in productivity for firms above the cutoff ($S_j \geq S^*$), while for firms below the cutoff ($S_j < S^*$) passthrough is positive asymmetric and increasing in productivity. In markets characterized by near constant returns to scale ($\alpha \to 1$) or less elastic labor ($\theta \to 0$), that cutoff goes to zero and passthrough will be negative asymmetric and decreasing in productivity and size for all firms. For example, Berger *et al.* (2019) use data from the United States to estimate α in a similar model of oligopsonistic competition in labor markets and find a value of 0.98, which for reasonable values of θ implies that passthrough is decreasing in productivity and negative asymmetric.[8] This coincides quite closely with our empirical results below.

Discussion

It is clear that in a simple model of imperfect labor markets, some predictions for passthrough are invariant across specifications ($\epsilon_A^w > 0$) while others depend critically on the nature of the labor supply curve (such as whether passthrough is increasing or decreasing in productivity). However,

[8] Estimates of average firm-level labor supply elasticities typically range between 4 and 6. Azar *et al.* (2019) find an average elasticity of 5.8 for US labor markets, while in Section 8 we find an average elasticity in this data of 5.7. In both cases market shares are small, so $\epsilon_W^L = \theta(1 - S_j)$ implies a value for θ of approximately 5.

knowledge of the labor supply curve is not enough to predict passthrough, nor does an estimate of the passthrough elasticity necessarily allow mapping out the labor supply curve. In fact, one can decompose the passthrough elasticity into the component due to the effect of productivity on labor requirements, and the effect of changes in labor requirements on the wage. Formally, the passthrough elasticity can be written as

$$\epsilon_A^w = \frac{dW}{dA}\frac{A}{W} = \frac{dW}{dL}\frac{L}{W}\frac{dL}{dA}\frac{A}{L} = \frac{\epsilon_A^L}{\epsilon_w^L}, \tag{4}$$

where ϵ_A^L is the elasticity of labor demand with respect to firm productivity, and ϵ_w^L is the labor supply elasticity. This implies that the passthrough elasticity is inversely related to the labor supply elasticity, such that (holding ϵ_A^L fixed) firms facing lower labor supply elasticities will have higher passthrough elasticities. This relationship is intuitive: if the labor supply elasticity is infinite, as in a perfectly competitive labor market, the passthrough elasticity will be zero and idiosyncratic firm shocks will have no effect on wages. Given that optimal wages in this setting are given by a markdown from marginal productivity of labor, MPL, such that $W = \mu MPL$ where $\mu = \epsilon_W^L / \left(\epsilon_W^L + 1\right)$, we might expect that firms with greater market power (greater wage markdowns) exhibit higher degrees of passthrough. If larger more productive firms tend to be on less elastic portions of their labor supply curve, then we should also see larger and more productive firms have larger passthrough elasticities.

However, the passthrough elasticity also depends on the characteristics of the labor demand function, itself a function of both the production and labor supply functions. If the firm's labor demand elasticity, ϵ_A^L, is also decreasing in productivity (as is the case in the market power example above), then we may see either positive or negative asymmetry in passthrough. Given parameter values of $\theta \approx 5$ and $\alpha > 0.9$, passthrough will be always negative asymmetric and decreasing in productivity, and market share because the slope of ϵ_A^L with respect to A_j and S_j is negative and greater in absolute value than the slope of ϵ_W^L. Equation (4) also implies that we can also use knowledge of two elasticities to make inferences about the third, which we do in Section 8 to obtain estimates of the labor supply elasticity.

Another key implication of these models is that estimation of passthrough will be complicated by a selection bias problem. As mentioned above, the main passthrough mechanism arises from firms who have received productivity shocks choosing to move up or down the labor supply curve by changing the wage offered to their workers. Attempts to estimate this relationship using data generated by this model will be complicated by the fact that data on wage and productivity changes will under-sample firms which shed workers after a negative productivity shock. This bias will lead to underestimates of the passthrough of negative shocks relative to positive shocks, which is exactly what we find and control for in our empirical strategy.

The framework above provides us with several key theoretical predictions for our empirical exercise. First, passthrough from productivity shocks to wages should be positive. Second, empirical measures of passthrough (especially from negative shocks) will be biased towards zero. Third, given common parameter estimates, we should find that passthrough is decreasing in firm size, productivity and market share. Fourth, firms will pass negative shocks on to wages more than they pass positive shocks to wages. Note that the monopsonistic version of the model with atomistic firms provides the first two predictions, but not the last two. We test these predictions in our empirical application.

3 Data

Our main source of information is a matched employer-employee administrative data set from Statistics Denmark covering the years 1991 to 2010. We obtain worker-level information from the Integrated Database for Labor Market Research, which is an annual database containing employment and demographic information for the entire population of Denmark. From this data set, we obtain several key variables such as annual income and hourly wages for each job at which an individual worked during the year, total number of hours and days worked in each job, occupation, labor market status, position within the firm, age, gender, education, and tenure within the firm. Our data also contains an identifier that links workers with their spouse. This information will be crucial when estimating the first stage of the selection model we use in Section 4.3. Our main outcome variable is the log change of average hourly wages. Using hourly wages instead of annual income allows us to isolate the impact of a shock to firms' productivity on workers' hourly earnings separately from the change in the number of hours worked at that job during the year.

In our baseline sample, we consider workers who are 15 years and older, who are not working in the public sector, or who are not self-employed. We use this sample to estimate the wage setting and production models described in Sections 4.1 and 4.2 respectively. For our main regression estimates, however, we focus on a subset of full-time workers (defined as individuals who work 30 or more hours per week) whose annualized total labor earnings are above 30,000 Danish kroner (about

4,600 US dollars in 2010). These restrictions leave us with 8.98 million worker-year observations for our primary analysis.

We match this individual-level panel to a firm-level panel—the Firm Statistics Register—which contains annual accounting and input use data for the universe of the Danish private sector.[9] The key firm-level variables we use are annual revenue, value added, capital stock, expenditure on intermediate inputs and materials, and employment (in full-time equivalents), as well as firm age, geographic location, and industry. This data allows us to construct robust measures of TFP, following the methods developed by Levinsohn and Petrin (2003), Ackerberg *et al.* (2015), Gandhi *et al.* (2020), and others. We drop firms that are not matched with any individual in our sample of workers. We also discard firms with non-positive or imputed measures of sales, employment, and other key variables.[10] This leaves us with around 45,000 firms per year, most of which have been in operation for at least 10 years. Appendix Table A.1 shows selected summary statistics of our sample of workers and firms.

4 Empirical Strategy

In this section, we discuss our empirical strategy to estimate the passthrough from firms' shocks to workers' wages, which consists of three interconnected parts. First, we study a statistical model of wages that we use to separate the contributions of worker and firm characteristics in determining workers hourly wages (Section 4.1). Second, we discuss our TFP estimation method where we use the results from the statistical model of wages to control for observed and unobserved variation in the quality of the labor input employed by the firms (Section 4.2). Third, we discuss how we correct for the selection bias that arises from workers' endogenous job mobility decisions (Section 4.3).

4.1 Two-way Fixed Effect Model of Wages

We start by estimating a statistical model of wages that allows us to separate the contribution of workers observed and unobserved characteristics from the wage-setting policies of the firms where they work. We interpret the contribution of workers' characteristics as a measure of workers' *ability*

[9]More precisely, the Firm Statistics Register begins with manufacturing in 1995 and gradually adds other sectors, reaching universal coverage of the Danish economy in 2001. Our results do not change if we only consider data starting in 2001.

[10]Our TFP estimation procedure requires data from years $t-1$ and $t-2$ in order to recover productivity in year t. Thus, our final summary statistics and estimation sample consist of firms that are three or more years old.

which does not depend on the characteristics of their employer. This measure of ability will be a crucial input in our TFP estimation which we discuss in Section 4.2.

We consider a modified version of the additive worker-and-firm fixed effect model proposed by AKM in which we assume that the log hourly wage, w_{ijt}, of an individual i working in firm j in period t is given by

$$w_{ijt} = \underbrace{\alpha_i + X_{it}\Gamma_t}_{\text{Ability units}} + \underbrace{\psi_{j(i,t)t} + \xi_{ijt}}_{\text{Per-unit ability price}} \tag{5}$$

where α_i is an individual fixed effect, X_{it} is a set of worker observable characteristics, $\psi_{j(i,t)t}$ is a firm-by-time fixed effect that identifies the firm j in which worker i is employed in period t, and ξ_{ijt} is a residual that is uncorrelated to worker or firm characteristics. In this way, we are able to separately identify the component of hourly wages that is due to the fixed and time-varying characteristics of the worker—which we refer to as ability units—from the component of hourly wages that is due to differences across firms and time—which we refer to as the time-varying per-unit ability price paid by the firm. We allow the parameters on individual observable characteristics, Γ_t, to vary with time in order to capture potential changes in the returns to education, occupation, or position within the firm.

Our specification differs from the standard two-way fixed effects regression model commonly used in the literature in two crucial aspects. First, most papers use annual labor earnings as their dependent variable, which might confound variations in the wage rate received by a worker and the number of hours worked by an individual during the year. This may be particularly relevant for workers with weak labor market attachment or those who transition between jobs during a year. For this reason, researchers have opted to discard workers with annual labor earnings below a certain minimum threshold.[11] Our data set contains detailed information on the hours worked and hourly wages for each individual-firm pair during a year, thereby allowing us to use average hourly wages as the main dependent variable.

Second, we do not impose that the contribution of firm characteristics to workers' wages is fixed, as in the standard AKM case, but rather allow it to be time-varying, as indicated by the time subscript on $\psi_{j(i,t)t}$. Adding time-varying firm effects is a necessary extension for this analysis, as our main interest is how variation in firm-level productivity over time affects worker wages. This modification allows the possibility of workers responding to firm-level shocks by moving across

[11] Typically this minimum threshold is set to a proportion of the total amount of income that a person would earn working at the minimum wage during a fraction of the year (Song *et al.*, 2019).

firms, and is consistent with the notion that firms' idiosyncratic productivity shocks, or other changes in firms' characteristics, may impact workers' wages.[12]

As in the standard AKM method, worker and firm-time fixed effects can only be identified within a connected set of firms that are linked through employment transitions. In order to estimate the firm-by-year fixed effects in Equation (5), we use information on all of the firms in which an individual worked during a given year, along with the corresponding wages and hours. Hence, in our data set, an individual can appear in different firms within the same year working at different hourly wages. Multiple worker-year observations increase the number of between-firm connections, the number of individual-level observations for each worker, and the size of the connected set.[13]

Since our dependent variable is the log of hourly wages, we consider all worker observations when estimating Equation (5), including full- and part-time jobs. This is important for the estimation of firm-level TFP: if we were to restrict our analysis to only full-time workers, or to only a worker's primary job, we would be undercounting the labor input for firms that use a higher proportion of part-time workers (which may vary with firm productivity).

We estimate the model in Equation (5) using the largest connected set of firm-time observations which includes 94% of the firms and 99% of all of the workers in our original sample.[14] In our estimation, we consider a rich set of worker-level observables including dummies for occupation, education, and position within the firm, as well as continuous measures of labor market experience and tenure within the firm, most of which are typically absent in other administrative data sets.

[12]As we further discuss in Appendix B, to identify the parameters of Equation (5), we require that labor mobility is not correlated with the residual ξ_{ijt}. However, we do allow workers to switch firms in response to shifts in $\psi_{j(i,t)t}$, thereby allowing the passthrough from firm productivity to wages to play a role in worker mobility decisions. The standard AKM model with time-invariant fixed effects assumes there is no such relationship and is thus inconsistent with our analysis. A few other papers also allow for time-varying coefficients in AKM regressions. For instance, Bagger *et al.* (2014) allow for occupation-firm fixed and firm-time fixed effects in their wage model and Bagger and Lentz (2019) incorporate time-varying firm-level observables into their estimation. Our paper is closely related to Engbom and Moser (2020) and Lachowska *et al.* (2020) who estimate a wage equation with time-varying firms fixed effects as we do in Equation (5). Gregory (2019) analyzes the growth of labor earnings in the context of a two-way fixed effect regression model, implicitly assuming a time-varying firm fixed effect.

[13]Holding multiple jobs in a particular year is quite common among workers in our sample: 54.4% of workers have held a second job at least once while 4.7% of workers have held three or more jobs. In our sample, we consider a worker's top three jobs in a given year (defined by total hours worked that year). It is important to note that, although using multiple firm-year observations per worker improves the accuracy of our estimates, it is not necessary for identification of the model.

[14]In Appendix B, we provide a graphical representation of how we construct our connected set using all job observation for each worker in the sample. Importantly, if we restrict our sample to only include the firm that provides the largest labor earnings for each worker (defined by total annual earnings), the largest connected set decreases in size, covering only 89% of firms.

Similarly to Card *et al.* (2013), we allow for the effect of education, occupation, and worker position within the firm to change over time in order to capture both the effects of time-varying observable individual characteristics and aggregate trends such as skill-biased technical change and outsourcing.[15]

We use the estimated coefficients of Equation (5) in two ways. First, as we explain below, the estimates of $\hat{a}_{it} = \hat{\alpha}_i + X_{it}\hat{\Gamma}_t$ are time-varying measures of worker i's ability which are independent from their relationship with the firm where they work. We use these estimates to construct an ability-adjusted measure of labor input for our TFP estimation. Second , we define the *ability-adjusted log hourly wage,* as

$$\hat{w}_{ijt} = \psi_{j(i,t)t} + \xi_{ijt}, \tag{6}$$

which is the component of worker i's hourly wage that is specific to their employment relationship with firm j in year t. We use the change in $\hat{w}_{ijt}$ as our main dependent variable in the regression analysis in Section 5.

4.2 TFP Estimation

One of the main challenges in studying the passthrough from firms' shocks to workers' wages is to finding exogenous sources of variation in firms' outcomes. The literature has proposed several measures such as variation in value added (Guiso *et al.*, 2005), export demand shocks (Garin *et al.*, 2018), or cash windfalls from patent allowances or government grants (Kline *et al.* (2019) and Howell and Brown (2020)). In this paper, we instead estimate shocks to firms' TFP using a dynamic structural model of firm production. Our method borrows from the flexible estimation approach proposed by GNR. We depart from their approach, in that we allow labor inputs to adjust dynamically in response to productivity shocks, and correct for unobserved variation in labor input quality using the estimates from the fixed-effects wage model described in Section 4.1.

There are two main challenges when identifying a firm's productivity shocks. First, since we are interested in how unanticipated shocks to the firm are passed on to wages, we need to separately identify exogenous changes in firm productivity from endogenous shifts in inputs and output. This is important since wages may be correlated with changes in capital stock or employment as well

[15] As shown in Appendix B, our estimates are in line with other studies that implement the AKM estimator (see for instance, Sorkin (2018), Song *et al.* (2019), and Lamadon *et al.* (2019)). We find that around 48% of the variance of the log hourly wages is accounted for by workers' observed and unobservable characteristics, 16% is accounted for by firms' time-varying characteristics, and sorting accounts for almost none of the variation in hourly wages.

as changes in productivity. The main difficulty arises from the fact that firms adjust their capital stock, employment, and other inputs in response to those same exogenous productivity shocks.[16] Failing to control for these correlations by using raw or residualized measures of revenues, sales or value added as proxies for the underlying firm shocks is thus likely to lead to biased estimates of passthrough.

Second, we need to ensure that our productivity estimation method is consistent with the analysis in the rest of the paper. In particular, we need to recover firms' TFP without relying on the assumption that labor markets are perfectly competitive or that firms are price-takers in labor markets, as both preclude the possibility of passthrough from idiosyncratic productivity shocks to wages. We also cannot assume that labor is a "predetermined" input like capital, since our empirical analysis hinges on the observation that labor inputs adjust in response to contemporaneous productivity shocks. Ideally we also want to avoid making any parametric assumptions about the shape of the production function, such as assuming it is Cobb-Douglas or CES, as this implicitly assumes a particular relationship between productivity and input demand (ϵ_A^L) which would potentially bias our estimates of the passthrough elasticity.[17]

With these considerations in mind, we start by examining a general representation of a firm-level gross production function in log-levels:

$$y_{jt} \quad = \quad f\left(k_{jt}, \ell_{jt}, m_{jt}\right) + \nu_{jt},$$

where ν_{jt} is the Hicks-neutral total factor productivity of firm j in period t. We assume that ν_{jt} is given by $\nu_{jt} = \omega_{jt} + \epsilon_{jt}$, where ω_{jt} is the persistent component of firm productivity, which is assumed to be first-order Markov and is given by $\omega_{jt} = \mathbb{E}[\omega_{jt}|\omega_{jt-1}] + \eta_{jt}$, where η_{jt} is a shock to the *persistent* component of firm's productivity, and ϵ_{jt} is an i.i.d. ex-post *transitory* shock that is uncorrelated with adjustments in inputs. In what follows, we use the terms *persistent shock* and *transitory shock* to refer to η_{jt} and ϵ_{jt}, respectively. To identify these shocks, we impose standard assumptions on the firms' decisions timing and information sets.[18] We allow the function

[16] This is the *transmission* bias problem, which has been a central concern of the TFP estimation literature going back to Marschak and Andrews (1944).

[17] This is especially important when we want to examine asymmetry and heterogeneity in the relationship between the productivity distribution and wages across firms and time.

[18] Following GNR, we assume that capital K_{jt} is a "predetermined" input that is fixed in period $t-1$, and that intermediate materials M_{jt} is a flexible input chosen every period. We depart from their framework in allowing labor L_{jt} to be a dynamic input which is allowed to depend arbitrarily on η_{jt} and L_{jt-1} through adjustment costs or other factors, while GNR assumes that labor is predetermined like capital. The timing of the model is such that

$f(.)$ to represent a general and unknown relationship between output and inputs, subject to weak assumptions on differentiability and concavity, and estimate it non-parametrically following the strategy outlined in GNR.

As is standard in the literature (Syverson, 2011), we measure Y_{jt} as real revenues, K_{jt} as the real value of the capital stock (using the perpetual inventory method), and M_{jt} with the real value of intermediate input expenditures.[19] We want to be especially careful about how we measure labor inputs L_{jt} since our goal is to estimate the relationship between wages, employment and firm productivity. The most straightforward approach is to use total labor hours or the number of workers employed at the firm. Neither of these measures is ideal however, as cross-sectional differences in the quality or composition of workers across firms will be loaded into productivity (ν_{jt}). Similarly, changes in the quality of a particular firm's workforce over time, possibly driven by productivity shocks, will also be interpreted as changes in ν_{jt}. For example, if a firm replaces a full-time janitor with a full-time engineer, the firm's output will likely go up, while the number of hours or employees will remain fixed. This will introduce significant bias into any estimates of firm productivity.

Another possibility is to use the total wage bill or labor costs of the firm. In this case, a firm that uses more engineers than janitors will have a larger wage bill, potentially controlling for the difference in ability of these types of workers. This approach implicitly assumes that wages are perfectly correlated with worker ability, and that labor markets are perfectly competitive, neither of which are appropriate in our context. First, there is substantial evidence that firms play an important role in the determination of wages and that workers with similar characteristics receive different wages at different firms.[20] Second, if labor markets are perfectly competitive, we should not expect to see any passthrough from idiosyncratic TFP shocks to wages.

firms enter period t knowing K_{jt}, L_{jt-1}, and, ω_{jt-1}. They then observe $\eta_{j,t}$ and choose L_{jt} and M_{jt} (which does not depend on M_{jt-1}). After the input decisions are set, the firm observes ϵ_{jt}. We assume that firms can adjust wages in response to both shocks, but that firms are price-takers in output markets and the market for intermediate materials.

[19] Our measure of TFP is "revenue" TFP rather than "quantity" TFP and thus contains both variation in production efficiency, as well as potential variation in output demand. We do not see this as a problem in our context, as we are agnostic about the source of the firm shock, as long as it is exogenous to the variations in inputs. We allow firms to adjust wages in response to shocks to both efficiency and demand, as both of these represent measures of firm-level risk that may be passed on to workers' wages. We choose to estimate revenue TFP since it allows us to include firms from the service sector, which accounts for most of the Danish employment and economic activity.

[20] For instance, several papers using the AKM approach to decompose wages find that around 10% of the dispersion of workers' wages is accounted for by fixed differences across firms. See for instance Barth *et al.* (2016), Song *et al.* (2019), and Engbom and Moser (2018). Our estimates show that firm-level wage setting accounts for between 16% and 52% of the overall variance in log wages.

In order to address these concerns, we use the estimates derived from our AKM model to net out the effect of firms on the wage bill and control for observed and unobserved heterogeneity across workers while remaining agnostic about the labor market conditions that induce the distribution of wages we observe in the data. In particular, the estimated value of the individual fixed effect and observable characteristics from Equation (5), $\hat{\alpha}_i + X_{it}\hat{\Gamma}_t$, is a measure of the "ability" of the worker. Importantly, this measure of ability is independent from (but potentially correlated with) the characteristics of the firm that employs the worker (which are captured by the firm-time fixed effect, $\psi_{j(i,t)t}$). Using this measure for all workers in a firm, we define the *ability-adjusted labor input* as

$$A_{jt} = \sum_{i \in J_t} \exp\left(\hat{\alpha}_i + X_{it}\hat{\Gamma}_t\right) H_{ijt},$$

where J_t is the set of workers in firm j in period t, and H_{ijt} is the number of hours worked by individual i in firm j in period t. Using these estimates, our ability-adjusted measure of firm productivity comes from estimating

$$y_{jt} = f(k_{jt}, a_{jt}, m_{jt}) + \nu_{jt},$$

where $a_{jt} = \log A_{jt}$. Note that the estimation procedure allows a_{jt} to be correlated with productivity ν_{jt} via η_{jt} and ω_{jt-1} but not with ϵ_{jt}.[21]

4.3 Selection Model

Our main empirical analysis focuses on the impact of firm shocks on wages for workers that maintain a stable employment relationship with their firm. However, a worker's decision to stay in a firm is obviously endogenous and may depend on the shocks affecting the firms. Ignoring this endogenous selection in the sample of "stayers" will likely lead to biased passthrough estimates. To see this is the case, suppose that after a negative shock, a firm decides to cut wages in order to reduce costs. If workers are more likely to leave a firm when faced with large wage cuts, then focusing only on those workers who stay—and thus, are less likely to face a large wage drop—would bias our estimates toward zero, thereby understating the degree of passthrough from firms shocks to wages. Through the lens of our model, this bias arises from the firm's movement down the labor supply curve in response to a negative productivity shock.

[21] Appendix Tables A.3 and A.4 show cross sectional moments of the distribution of log-TFP, TFP growth, and TFP shocks.

In order to correct for this bias, we consider a standard selection model, as in Heckman (1979). In particular, we assume that the probability of staying in a firm between periods is given by $Pr(D_{ijt} = 1) = \Phi(U\delta)$, where $D_{ijt} = 1$ if worker i remains at firm j and U is a vector of worker and firm observables. We follow a standard two-step procedure by obtaining estimates of $\hat{\delta}$ and computing the inverse Mills ratio, denoted by $\hat{\lambda}$, which we include in our passthrough regressions. Our identification strategy relies on including observable variation in U which determines the probability that workers will stay or leave their firm, but does not affect the growth rate of workers' wages should they choose to stay at the firm in that period.

We obtain this variation from the family linkages available in our data to create, for each worker, a set of time-varying marital status indicators and—for those with working spouses—measures of their spouse's employment status, and firm shocks. Specifically, we include indicators for marriage status, separation, change of spouse, and whether or not the individual's spouse is working if married. This last term is interacted with other spousal information, including their log wage, change in log wage, firm TFP and log TFP change, age, experience, and whether or not the spouse stayed in their firm for that period. We exclude information about the spouse of a worker if the couple is working at the same firm. This gives us the following first-stage probit model,

$$\Pr(D_{ijt} = 1) = \Phi(U\delta) = \Phi\left(\beta_p^d x_{ijt} + \beta_n^d x_{ijt} \times \mathbb{I}_{x_{jt}<0} + X_{it}\Omega^d + Z_{jt}\Gamma^d + T_{it}\Omega^d + E_{it} \times S_{it}\Psi^d\right), \quad (7)$$

where x_{ijt} is a measure of the productivity shocks affecting the firm j where worker i is employed. X_{it} and Z_{ijt} matrices containing worker- and firm-level observables respectively, T_{it} is the set of marital status indicators, E_{it} is an indicator that equals 1 if the worker's spouse is employed, and S_{it} is a vector of observables for the spouse and the spouse's firm, as described above. The indicator function $\mathbb{I}_{x_{jt}}$ captures the asymmetric impact of positive and negative TFP shocks to the firm on the probability that a worker stays in the firm. The assumption underlying our choice of instruments is that when a worker changes their marital status or their spouse has an income shock or employment change, this will affect the worker's decision to keep working at the current firm. However, these changes do not affect the elasticity of (firm-level) wages to productivity in their own firm.

The estimation results of Equation (7)—shown in Appendix Table A.2—indicate that positive productivity shocks increase a worker's probability of staying at the firm, whereas negative shocks does the opposite. We also find that that men, older workers, and workers who have recently changed spouses are more likely to leave a firm, while being married, having a longer tenure in the firm, having a spouse who stays at their firm, and having a spouse who works in a firm experiencing a positive TFP shock, increase the probability of staying. From the estimates of Equation (7), we obtain the inverse Mills ratio which we use in the following section.

5 The Passthrough from Productivity Shocks to Wages

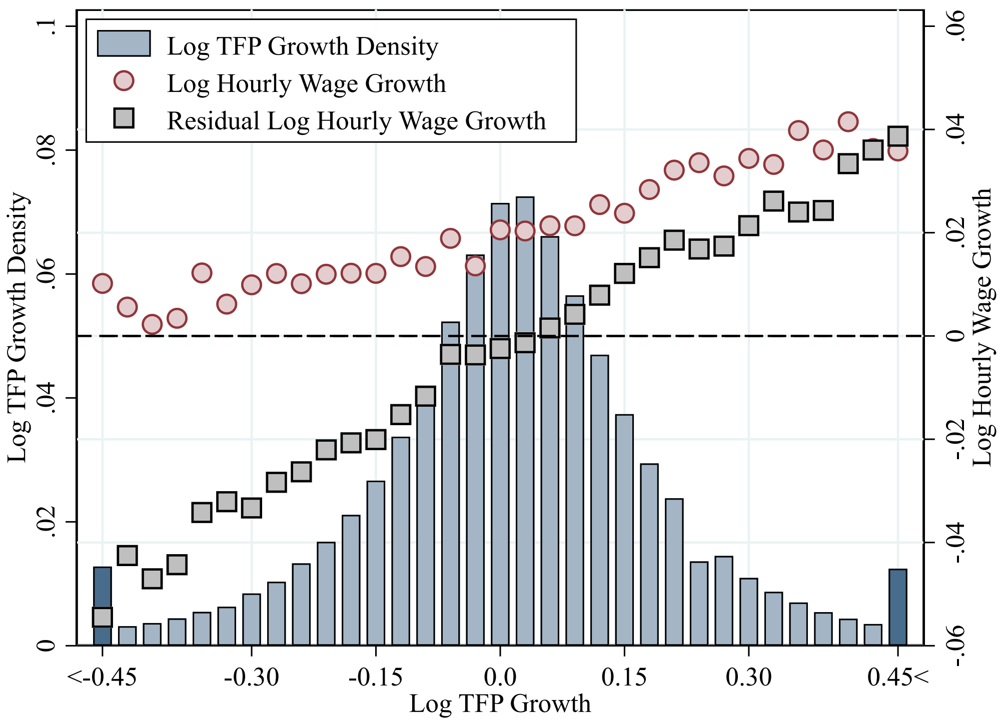
In this section, we discuss our main empirical results relating the changes in workers' hourly wages to different measures of firm-level productivity shocks. Before we dive into our empirical results, however, it is useful to provide a simple illustration of our main findings. Figure 1 shows the relation between log firm productivity growth and log hourly wage growth for workers. To construct this figure, we partition our sample of firms into equally sized bins based on their productivity growth between periods t and $t-1$, and plot the corresponding density on the left axis. Then, within each bin, we calculate two measures of wage growth for stayers: the average change in log hourly wages (red circles) and the average *residual* change in log hourly wages after we have controlled for workers' endogenous mobility decisions (black squares).

Two aspects of the figure are worth noticing. First, log hourly wage growth is positively correlated with firm-level productivity growth, especially when firms experience positive growth, but appears to be insulated from negative productivity growth. In fact, average hourly wage growth is positive across the entire TFP growth distribution (all of the red circles are above zero) even for firms experiencing large negative changes in productivity. This would suggest that hourly wages are subject to downward rigidity and that, although there is some passthrough from productivity to wages, it is small and mostly due to positive shocks to productivity.

Second, when controlling for worker's endogenous mobility decisions, we find a significant increase in the relationship between wage growth and TFP growth (black squares), which is mostly driven by an increase in the elasticity of (residual) wage growth among firms receiving negative productivity shocks. We can thus conclude that controlling for endogenous worker mobility generates a substantial increase in the passthrough of workers' wages with respect to fluctuations in firm productivity.[22]

[22] Adjusting for selection affects the passthrough from firm shocks across the entire distribution of hourly wage growth. As we show in Figure A.1 in Appendix A, not controlling for selection would lead one to conclude that for workers in firms experiencing a 30% decline in productivity, the median of the wage growth distribution is roughly 0 while the 90th percentile is 6% growth in wages. After controlling for selection, we find that the median worker in those firms instead experienced a 2.5% decline in hourly wages, whereas workers in the 90th percentile experienced

Figure 1 – Passthrough from Firms' Productivity Growth to Workers' Wages



Note: Figure 1 is based on a pooled sample of firms and workers between the years 1996 to 2010. The blue bars show the share of firms within different bins of the log TFP growth distribution (left y-axis). To construct the plot, we separate firms into 41 equally spaced bins between -.45 and 45. To avoid the disclosure of any sensitive information, the left- and right-most bins, marked in darker blue, encompass the remaining left and right tails of the distribution. The red circles show the average log hourly wage growth for all workers employed by firms within a bin (right y-axis). The black squares show the average hourly wage growth after controlling for worker characteristics, firm characteristics, and endogenous selection as explained in Section 4.3 (right y-axis).

Baseline Regression Results

Our main passthrough estimates are based on a series of worker-panel regressions that relate the change in workers' hourly wages to firms' idiosyncratic productivity shocks.[23] More precisely, our baseline specification is

$$\Delta \hat{w}_{ijt} = \alpha + \beta^{\nu} \Delta \nu_{jt} + Z_{jt}\Gamma + X_{it}\Omega + \rho \hat{\lambda}_{ijt} + \delta_t + \zeta_{ijt}, \tag{8}$$

where $\Delta \hat{w}_{ijt}$ is the change in the ability-adjusted log hourly wage of individual i in firm j—defined in Equation (6)—between periods t and $t-1$, and $\Delta \nu_{jt}$ is the change in the log TFP for firm j

an increase in hourly wages of 3%.

[23] Appendix Table A.5 shows selected statistics for the main variables we use in our analysis. In our sample, the standard deviation of log wage growth for stayers is 0.18 (column 1), which is half of the dispersion in wage growth for switchers (column 2). By comparison, Kurmann and McEntarfer (2019) report an interquartile range of 11 log points (13 log points in our sample). In terms of firms' productivity, we find a standard deviation of the persistent component of firms' productivity shocks equal to 0.27. This is larger than other estimates in the literature. For instance, Guiso and Pistaferri (2020) report a standard deviation of firms' persistent shocks of 0.05. As we show in this section, however, our passthrough estimates are quite in line with the rest of the empirical literature, indicating that in our sample, firms provide a larger degree of insurance.

between periods t and $t-1$. The matrices Z_{jt} and X_{it} control for firm characteristics (e.g., lagged productivity, firm size, firm age, etc.) and worker characteristics (e.g., gender, age, tenure in the firm, wage level, etc.), respectively, δ_t is a time fixed effect that controls for aggregate fluctuations in the economy, and ζ_{ijt} is the residual. We also include the estimated inverse Mills ratio, $\hat{\lambda}_{ijt}$, obtained from the first-stage estimates of Equation (7). As we show below, controlling for selection has important implications for the value of β^{ν}, our main parameter of interest, which measures the *average* passthrough elasticity from changes in firm productivity to wages.

Table I displays our main results. Column (1) shows that there is positive and significant passthrough from firms' TFP shocks to hourly wages. Quantitatively, an elasticity of 0.076 implies that a worker employed in a firm that experiences an increase in productivity of one standard deviation (about 0.24 log points in our sample) receives an increase in average hourly wages of 0.018 log points. This change amounts to \$1,075 for the average full-time worker in Denmark (see the bottom panel of Table I) or about about 1.8% of the average annual income.[24] Given that in a typical year around 20% of firms in our sample (which employ around 25% of all private sector workers in Denmark) experience a change in productivity of at least one standard deviation away from the mean, we conclude that idiosyncratic fluctuations in firm productivity represent an important source of fluctuations in workers' income.

We then analyze the passthrough of positive and negative productivity changes to wages separately. We do so by interacting $\Delta\nu_{jt}$ with an indicator function, $\mathbb{I}_{\Delta\nu_{jt}<0}$, that is equal to one if the corresponding productivity change is negative, as in the following specification:

$$\Delta\hat{w}_{ijt} = \alpha + \beta^{\nu}_{p}\Delta\nu_{jt} + \beta^{\nu}_{n}\Delta\nu_{jt} \times \mathbb{I}_{\Delta\nu_{jt}<0} + Z_{jt}\Gamma_t + X_{jt}\Omega_t + \rho\hat{\lambda}_{ijt} + \delta_t + \zeta_{ijt}, \tag{9}$$

where β^{ν}_{p} measures the average passthrough from a positive change in ν_{ijt}, whereas $\beta^{\nu}_{p} + \beta^{\nu}_{n}$ is the average passthrough from a negative change in ν_{ijt}. The results are shown in column (2) of Table I. First, notice that the coefficient for a positive change is smaller than the average elasticity displayed in column (1), but still statistically and economically significant. Second, and more importantly, the elasticity of wages to a negative change in productivity is significantly larger and equal to 0.11. This indicates that a one standard deviation change in TFP, conditional on this change being negative, generates a decrease in annual wages for the average Danish worker of \$1,600, which

[24]For this calculation, we multiply the value of β^{ν} times the standard deviation of firm productivity growth times the average annual wage of the workers in the corresponding sample. In what follows, we express the impact in terms of 2010 US dollars.

Table I – Passthrough from Firm TFP shocks to Wages

Dep. Variable	Change in Log Hourly Wages, $\Delta\hat{w}_{i,j,t}$							
	Selection Corrected				Uncorrected			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Specification:	All	Pos/Neg	All	Pos/Neg	All	Pos/Neg	All	Pos/Neg
$\Delta\nu_{jt}$	.076***	.060***			.046***	.062***		
	(.004)	(.004)			(.003)	(.004)		
$\Delta\nu_{jt} \times \mathbb{I}_{\Delta\nu_{jt}<0}$		.053***				−.032***		
		(.005)				(.005)		
η_{jt}			.077***	.061***			.033***	.044***
			(.007)	(.004)			(.004)	(.004)
$\eta_{jt} \times \mathbb{I}_{\eta_{jt}<0}$				.070***				−.022***
				(.007)				(.009)
ϵ_{jt}			.034***	.025***			.034***	.032***
			(.003)	(.005)			(.003)	(.004)
$\epsilon_{jt} \times \mathbb{I}_{\epsilon_{jt}<0}$				.018**				.007
				(.008)				(.009)
$Mills_{it}$	−.219***	−.278***	−.188***	−.262***				
	(.014)	(.015)	(.023)	(.013)				
R^2	.78	.78	.79	.79	.78	.78	.78	.78
Obs. (Millions)	6.47	6.47	6.47	6.47	6.47	6.47	6.47	6.47
Monetary Value of a Shock to Firm TFP (US$ 2010)								
$\Delta\nu_{jt}$	$1,075				$655			
$\Delta\nu_{jt} > 0$		$840				$873		
$\Delta\nu_{jt} < 0$		$1,579				$403		
η_{jt}			$873				$386	
$\eta_{jt} > 0$				$689				$504
$\eta_{jt} < 0$				$1,495				$252
ϵ_{jt}			$336				$353	
$\epsilon_{jt} < 0$				$252				$319
$\epsilon_{jt} > 0$				$436				$386

Table I shows a set of OLS panel regressions controlling for firm and worker characteristics. All regressions include firm-level controls (i.e., firm age, lagged firm TFP level, firm employment, and total firm ability), worker-level controls (i.e., a polynomial in age, lagged worker experience, lagged log wage level, lagged tenure in the firm, gender, and lagged log ability), the inverse of the Mills ratio to control for selection, and year fixed effects. All monetary values are in 2010 US dollars. $*p < 0.1, **p < 0.05, ***p < 0.01$. Robust standard errors are clustered at the firm-level.

is roughly twice the change in wages resulting from a positive productivity shock of the same magnitude. In other words, the passthrough from firms' shocks to wages is not only significant, but also asymmetric, with negative changes in firms' idiosyncratic productivity generating much larger declines in wages than positive changes in productivity. We refer to this as "negative asymmetric" passthrough. This negative asymmetry in passthrough corresponds with the predictions of our simple model where firms have market power and operate with nearly constant returns to scale.

Transitory and Persistent Shocks

We now turn to analyzing the impact of transitory and persistent shocks to productivity on wages. These two types of shocks can have a distinct impact on workers, as firms might be more likely to insure workers from variations in productivity that are perceived as transitory—e.g., a decline in sales because of unexpected bad weather—than from variations that are perceived as persistent—e.g., an increase in sales due to the implementation of a new online platform. Following the estimation approach introduced first by Guiso *et al.* (2005), most papers have consistently found that persistent shocks to firms have a significant impact on wages, whereas transitory shocks do not have a significant effect on wages (see Card *et al.* (2018) and Guiso and Pistaferri (2020) for recent reviews).[25] Here, we reevaluate the role of persistent and transitory shocks by including in our baseline specification the persistent and transitory components of firm productivity estimated in Section 4.2. In particular, we estimate

$$\Delta\hat{w}_{ijt} = \alpha + \beta^{\eta}\eta_{jt} + \beta^{\epsilon}\epsilon_{jt} + Z_{jt}\Gamma_t + X_{it}\Omega_t + \rho\hat{\lambda}_{ijt} + \delta_t + \zeta_{ijt}, \tag{10}$$

where β^{η} and β^{ϵ} are the elasticity of wages with respect to the persistent and transitory components of firms' TFP, respectively.[26] Column (3) of Table I shows the results. We find that although transitory and persistent shocks have a significant impact on hourly wages, wages are more than two times more responsive to persistent than to transitory productivity shocks.

We then separate the impact of transitory and persistent shocks into their positive and negative parts, as we do for TFP growth in Equation (9). We find a marked asymmetry between positive and negative shocks. In fact, as column (4) shows, the elasticity of wages to a negative persistent shock is twice as large as the elasticity to a positive persistent shock. In terms of annual earnings (bottom panel of Table I), a decline in η_{jt} of one standard deviation generates a decline in worker's annual labor earnings of \$1,495, whereas an increase in η_{jt} of the same magnitude generates an increase of \$689. Similarly, we find a negative asymmetric pattern for transitory shocks, with negative transitory shocks having a larger impact on wages than positive transitory shocks, although the

[25] One notable exception is Howell and Brown (2020), who find that a transitory cash flow shock to the firm significantly impacts workers' wages. The transitory shocks we study, however, differ from theirs in that a transitory cash flow can imply a persistent change in productivity if it leads to innovation, the purchase of new equipment, or the incorporation of new technologies.

[26] We estimate a separate first-stage probit model for every regression specification in this paper, depending on the firm shocks and the sample in question. In this case, we estimate $\hat{\lambda}_{ijt}$ from a separate first-stage regression on η_{jt} and ε_{jt} rather than $\Delta\nu_{jt}$.

magnitudes are much smaller than for persistent shocks.

Bias and Asymmetry

The evidence presented in Figure 1 suggests that the bias arising from endogenous worker mobility is large, significant, and asymmetric. In our context, selection bias will affect the passthrough estimates if the probability that a worker stays at their firm (and thus remains in our baseline sample for estimating within-firm passthrough) depends on the magnitude or sign of the firm shock. Intuitively, workers in firms that experience larger declines in TFP (and thus face larger declines in wages) will be more likely to leave their firm than workers in firms that experience smaller declines in TFP. In this case, we would expect our passthrough estimates for negative shocks to be biased toward zero.

To evaluate the extent of the bias, we repeat the previous analysis without correcting for worker selection induced by endogenous mobility decisions (i.e., we exclude the inverse Mills ratio from our regressions). The results are shown in columns (5) to (8) of Table I. As expected, we find that selection biases the estimated coefficient of firms' shocks on hourly wages toward zero. We also find that the bias is more significant for persistent than for transitory shocks. To see this, compare columns (3) and (7), where the elasticity to persistent shocks declines by more than a half for persistent shocks when we do not control for selection, but remains the same for transitory shocks.[27] Consistent with the intuition above, the passthrough estimates for negative shocks are the most affected by selection: if we were to ignore selection, we would conclude that negative persistent shocks have a passthrough elasticity of 0.022, which is six times smaller than the elasticity implied by our baseline selection-corrected estimates. These results would lead us to wrongly conclude that passthrough is positive asymmetric and wages are not responsive to negative shocks to firm productivity. Given the importance of properly controlling for selection, all of the results that follow include selection-correction terms.[28]

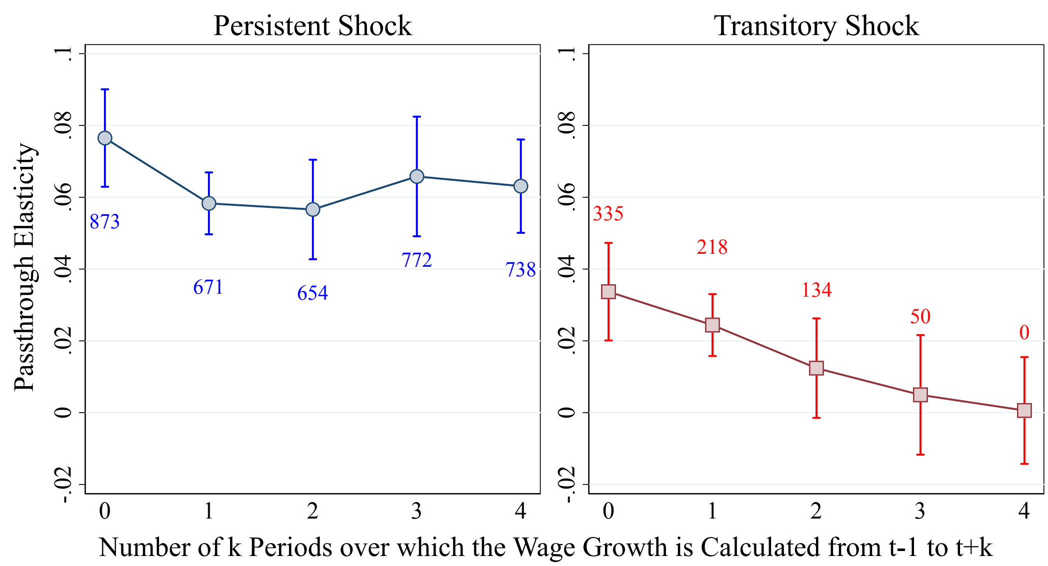
Persistence

We now discuss the long-term impact of firms' shocks on workers wages. Intuitively, if shocks to firms only translate into a short-lived increase in workers' wages (even when the shocks to firms

[27]This is consistent with the timing of our model of firm productivity, which assumes that inputs (including labor, though not wages) are fixed prior to observing ϵ_{jt}.

[28]In Appendix C, we explore the bias which results from removing each additional step of our empirical approach. In particular, we show that controlling for hours worked cuts passthrough estimates in half, while controlling for worker ability and using our measure of productivity shocks significantly increases estimated passthrough.

Figure 2 – Shocks to Firms Have a Long-Lasting Impact on Workers' Wages



Note: The left panel (right panel) of Figure 2 shows the elasticity of hourly wages to a persistent (transitory) shock to firms productivity. Each point on the graph is the elasticity coefficient from a separate regression where the dependent variable the change in workers' hourly wages different time-horizons (defined by $k \geq 0$). The vertical lines show 95% confidence intervals around those point estimates. In each plot, the numbers above and below the lines represent the monetary value of a shock of one standard deviation calculated using the corresponding elasticity. All monetary values (in 2010 US$) are calculated relative to the average annual labor earnings within the corresponding group.

are persistent), one should expect large contemporaneous passthrough (a positive and significant correlation between a TFP shock in period t with a change in workers' wages between t and $t-1$), but a smaller passthrough at longer horizons (for instance, a correlation between a shock to firms in period t and a wage change between $t+4$ and $t-1$ closer to 0). To study the persistence of passthrough, we modify our baseline specification in Equation (10) by extending the horizon of the wage change on the left-hand side to $t+k$ periods, where k can take values between 0—as in our baseline case—and 4. Importantly, we keep constant the period in which we measure firms' productivity shocks and other firm and worker observables.[29]

To simplify the exposition of our results, Figure 2 shows on the y-axis the elasticity of worker wages to a persistent or transitory shock to firm productivity at different horizons. Each point on the figure represents a passthrough coefficient from a separate set of first- and second-stage regressions. In both panels, the x-axis corresponds to the periods over which the wage growth is calculated and the vertical lines are 95% confidence intervals for the corresponding regression coefficient. The left panel shows that the passthrough from persistent TFP shocks is not only statistically significant in the first year—our baseline estimate—but also persists after 4 more

[29]Note that our selection correction procedure changes as well, such that we run separate first-stage regressions for each separate time horizon, where the dependent variable in the first stage is an indicator of whether the worker stayed at the firm for all $t-1$ to $t+k$ periods.

years, with only a small decay in magnitude. In contrast, short-lived transitory shocks have a much less persistent impact on workers' wages, although the effect does not disappear immediately, generating a small but still significant change in workers' wages, even 2 years after the shock.[30]

To summarize, in this section we have shown that idiosyncratic shocks to firms' productivity have a significant and persistent impact on workers' wages, which depend not only on the nature of the shocks (persistent versus transitory) but also on the sign (positive versus negative).[31] In the following sections, we complement these results in two ways. In the next section, we exploit the richness of our data set to explore how passthrough varies across workers and firms with different characteristics, and over time.

6 Heterogeneous Passthrough

As we have shown, the average passthrough from firm shocks to wages is significant and asymmetric. Still, it is possible that the overall effect masks substantial heterogeneity across firm and worker types. For example, as the theory presented in Section 2 implies, firms with different labor market power, productivity or size may pass shocks to their workers at different rates, which we analyze in Section 6.1. Similarly, in Section 6.2, we study whether workers of different ability, age, or tenure might be subject to different passthrough. Finally, in Section 6.3 we analyze whether passthrough is state dependent and changes with aggregate economic conditions. The main conclusion of this section is that the passthrough from firms' shocks to wages is highly heterogeneous and varies substantially across worker and firm groups, and over the business cycle. To conserve space, most of our discussion centers around the impact of persistent shocks to productivity but we present equivalent results for the impact of transitory shocks in Appendix A.

6.1 Firm Heterogeneity

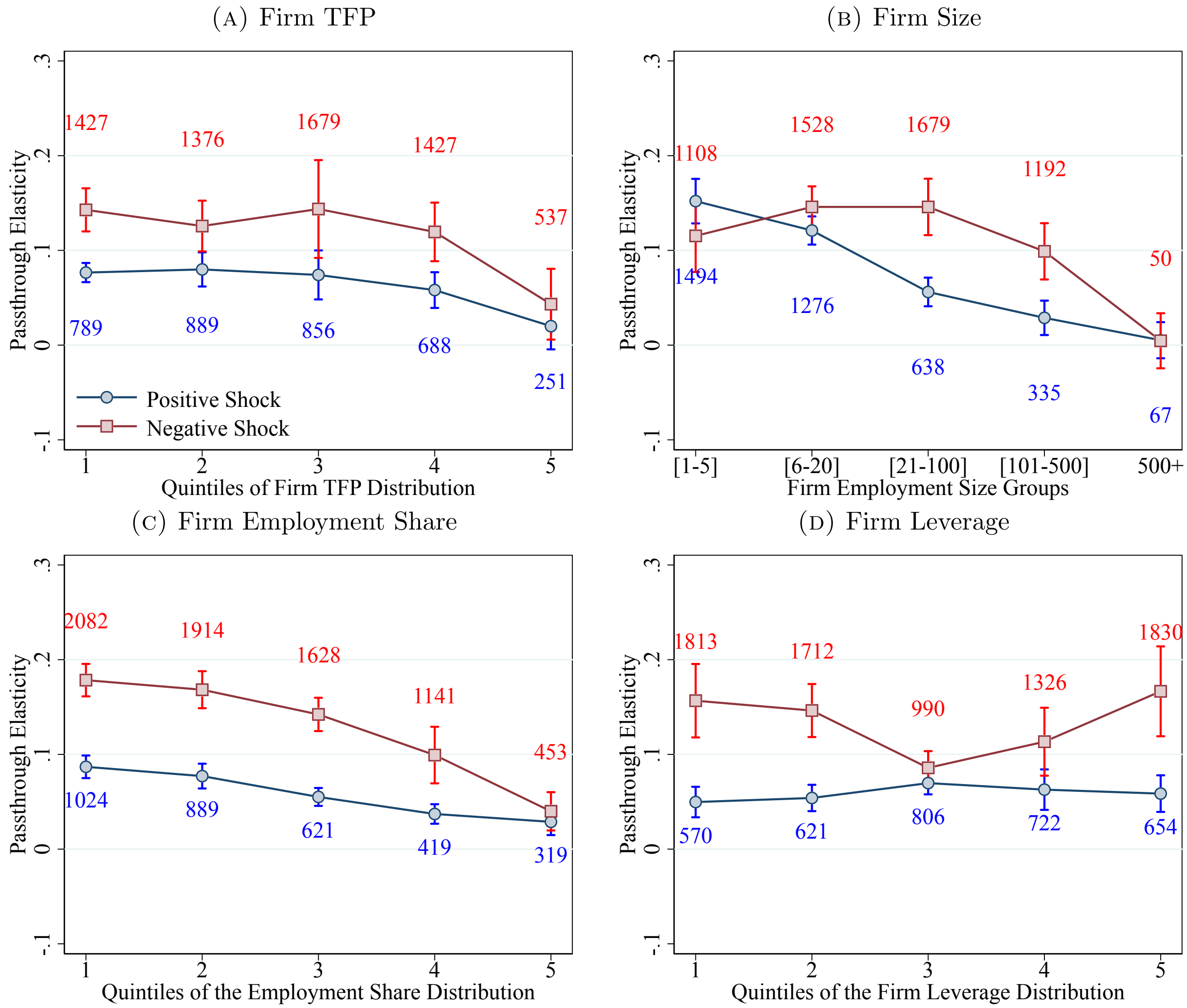
Firm Productivity

We first study whether firms with different productivity levels differ in their level of passthrough from shocks to wages. This would be the case if, for instance, firms have some degree of labor

[30] As we show in Appendix A, these results are robust to separating positive from negative shocks (Panel A of Figure A.2) or if we restrict our sample for all these estimates to a balanced panel of workers who stay in the same firm for four years after the shock (Panel B of Figure A.2).

[31] In Appendix D we separate productivity shocks into aggregate, industry and idiosyncratic components and show that our results are explained almost entirely by the idiosyncratic firm-level component. We also find that while negative industry shocks are passed on to wages on average, positive industry shocks are not.

FIGURE 3 – FIRM HETEROGENEITY: PASSTHROUGH FROM PERSISTENT SHOCKS TO FIRMS TFP



Note: Panel A of Figure 3 shows the elasticity of hourly wages across different workers employed in firms with different characteristics. Panel A shows the passthrough within quintiles of the TFP distribution and the corresponding value of a one standard deviation shock expressed in dollars of 2010. Panel B to D present similar statistics for workers employed in firms of different employment size, labor market share, and firm leverage.

market power such that high productivity firms face a more inelastic labor supply (as in the example in Section 2). As the elasticity of the labor supply decreases, greater wage increases are required to obtain the same increase in labor, thereby increasing the measured passthrough. Alternatively, if firms operate with nearly constant returns to scale, larger firms will also be on less elastic portions of their labor demand curve (lower ϵ_A^L) which may decrease passthrough, as shown in Section 2.1. Additionally, if larger or more productive firms have greater access to financial markets, one would expect the passthrough to decline with firm size and productivity, as highly productive firms can better insure themselves and their workers from productivity shocks, relative to low productivity firms. Our results are consistent with these last two interpretations. In fact, our estimates indicate that conditional on firm size, industry, and other firm- and worker-level characteristics, the wages of workers employed by low productivity firms are significantly more exposed to firm shocks than workers employed by high productivity firms, both for positive and negative shocks.

We show this by separating our sample of firms into quintiles by their (lagged) log TFP level, ν_{jt-1}. We then assign workers to their corresponding firms in a year and run our baseline specification separately within each group. Panel A of Figure 3 shows the results. We find that the passthrough from persistent shocks to firms (both negative and positive) is decreasing in firms' productivity, especially in the top three quintiles of the distribution. For example, workers employed at firms in the lowest productivity quintile gain (lose) \$789 (\$1,427), or 1.5% (2.8%) in annual income on average when their firm experiences a positive (negative) persistent shock of one standard deviation. Workers employed at firms in the highest quintile of the TFP distribution, on the other hand, see much smaller wage changes. On average, these workers gain \$251, or 0.4% in annual income (lose \$537, or 0.8% in annual income) when their firm experiences a one standard deviation positive (negative) persistent shock.

Size and Market Power

Several firm characteristics besides productivity might impact the passthrough from firms' shocks to wages. For instance, the theoretical models described in Section 2 suggest that both absolute and relative firm size may play a role in determining passthrough. Hence, in this section, we discuss how passthrough varies along these dimensions. In general, we find that conditional on workers and firm characteristics—including firm productivity—large firms generate a much smaller passthrough than small firms.

We start by separating our sample of firms into groups by total employment (in full-time equivalents) and then run our baseline regression within each group. Panel B of Figure 3 displays the results. In general, we find that small and medium-size firms generate much larger passthrough than large firms. In fact, the passthrough in firms with 500 or more employees is essentially equal to 0 for both positive and negative shocks. This indicates that very large firms are quite effective at insulating their workers from idiosyncratic firm-level risk.

It is possible that differences in passthrough across the firm-size distribution reflect differences across industries or locations—perhaps manufacturing firms tend to be larger and also have less passthrough. The passthrough might also vary across firms within labor markets due to differences in labor market power. Firms with greater labor market power will tend to have larger labor market employment shares (conditional on productivity) and be situated on more inelastic portions of their labor supply curve. We investigate this in Panel C of Figure 3 where we partition our firm sample into quintiles based on their employment share within an industry-municipality bin.[32]

As with total employment, the passthrough from positive and negative shocks is declining in labor market share. Quantitatively, workers employed in firms in the first quintile of the employment share distribution—i.e., small firms with around 0.6% of employment in their local labor market—gain $1,026 from a one standard deviation increase in persistent productivity, and lose $2,082 from a negative shock of the same magnitude. In contrast, workers employed by firms in the fifth quintile—large firms with around 10% of the employment of their local labor market—are better insured, experiencing gains (losses) of $319 ($453) from positive (negative) persistent shocks of one standard deviation. This heterogeneity in passthrough is consistent with the predictions of our model of market power and oligopsonistic competition, which links heterogeneity in passthrough directly to the firm's market share. Through the lens of the model, the monotonically negative empirical relationship between passthrough and market share suggests that labor markets are not very elastic and that firms operate at nearly constant returns to scale and enjoy some market power.

Financial Constraints

Finally, we study whether firms that are more financially constrained tend to have different passthrough than less financially constrained firms. Arguably, firms that are at or close to their borrowing constraint are less able to insure their workers after a negative productivity shock. To see whether this is the case, we measure financial leverage for each firm in our sample as the ratio of total (long- and short-run) debt to total firm assets.[33] We separate firms into quintiles of the financial leverage distribution and run our baseline regression within each group.[34] The results, shown in Panel D of Figure 3, indicate there is no monotonic relationship between passthrough and financial constraints. Instead, we find that firms in the middle quintile, with debt-to-asset ratios of roughly 0.7, have significantly less negative passthrough than both the high- and low-debt firms in the fifth and first quintiles of the leverage distribution, respectively. The passthrough from

[32]We calculate employment shares within each industry-municipality, where an industry is defined at the 2-digit NACE level https://www.nace.org/home. This is a fairly granular definition of a labor market, with the median firm within the top employment share quintile having around a 10% share of employment within that market. To avoid the disclosure of any sensitive information, we calculate the median share within a quintile as the average share for all firms between the 50 and 51 percentiles of the employment share distribution within each quintile. Quintiles 1 through 4 have a within quintile median labor market shares of 0.6%, 1.4%, 4.7%, and 6%, respectively.

[33]We take the measures of leverage as constructed by Friedrich and Zator (2020)

[34]The median debt-to-asset ratios for quintiles 1 through 5 are 0.37, 0.57, 0.69, 0.79, and 0.94, respectively.

positive shocks does not show significant variation across the leverage distribution.[35]

6.2 Worker Heterogeneity

Wages and Ability

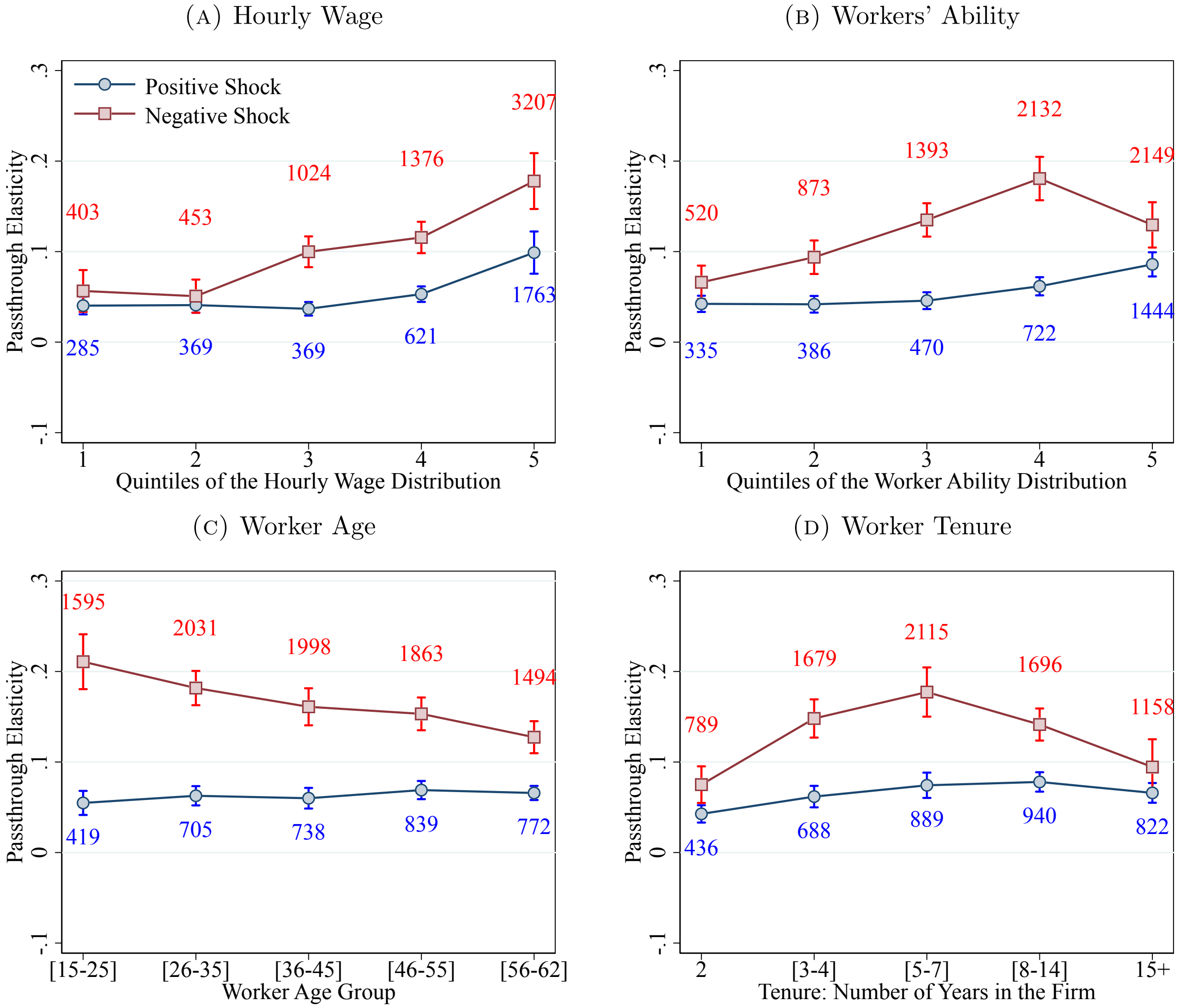
Workers at different income levels may also be differentially exposed to shocks affecting the firms where they work. Studying how the passthrough varies across the income distribution is important for at least two reasons. First, low-income workers are more likely to be credit constrained. To the extent that idiosyncratic shocks to firms represent an uninsurable risk, finding a higher passthrough for low-income workers might have significant welfare implications, even though the average passthrough is small. Second, variations in the passthrough across income levels might help to explain why individuals at the top and bottom of the income distribution seem to face larger fluctuations in labor earnings than individuals in the middle of the income distribution (Guvenen *et al.*, 2015). Overall, we find that high-wage and high-ability workers are more exposed to idiosyncratic shocks to firms' productivity than low-wage and low-ability workers.

We start by separating workers into quintiles based on their past hourly wage and estimate the passthrough from persistent and transitory shocks within each quintile. Panel A of Figure 4 summarizes our results. The differences in passthrough between low- and high-wage workers after a persistent shock to firms' productivity are substantial: the elasticity to positive shocks for workers in the fifth quintile of the distribution is more than twice as large as the elasticity for workers in the first quintile. Quantitatively, we find that workers at the fifth quintile of the distribution gain six times more in annual income than workers at the bottom quintile ($1,763 versus $285, or 1.9% and 0.8% of the within-group average annual income, respectively) when their firms receive a persistent positive shock to firms' TFP of one standard deviation. This difference is even more stark for negative shocks. Workers in the top wage quintile lose $3,207 in annual labor earnings after such a shocks, while those in the bottom quintile lose only $403.

We find a similar pattern when we look at worker "ability", as measured by the sum of a worker's fixed effect and time-varying observable characteristics, $\hat{a}_{it} = \hat{\alpha}_i + \hat{\Gamma}_t X_{it}$, derived from our AKM estimates. Panel B of Figure 4 shows these results. Similarly to the hourly wage, workers at the bottom of the ability distribution are much less exposed to firm shocks than those at the top of the distribution. In other words, high-wage workers experience larger gains and losses than

[35] We also analyze whether the passthrough varies across the firms' age distribution, but do not find significant differences in the passthrough for younger versus older firms.

FIGURE 4 – WORKER HETEROGENEITY: PASSTHROUGH FROM PERSISTENT SHOCKS TO FIRMS TFP



Note: Panel A of Figure 4 shows the elasticity of hourly wages across different workers' characteristics. Panel A shows the passthrough within quintiles of the hourly wage distribution and the corresponding value of a one standard deviation shock expressed in US dollars (2010). Panel B to D present similar statistics for workers in different quantiles of the ability distribution as measured by $\exp(\hat{\alpha}_i + \hat{\Gamma} X_{it})$, the age distribution, and the tenure distribution. We choose the tenure cutoffs so as to have groups of roughly similar size.

low-wage workers when their firms experience persistent TFP shocks. This is is consistent with the notion that labor earnings for high-income workers' is more linked to firm performance than for low-income workers.[36]

Tenure and Age

Workers may be more or less exposed to firm shocks, depending on their age and tenure within the firm. For instance, older workers are more likely to have accumulated general work

[36]Consistent with our baseline estimates, the quantitative effect of transitory shocks to TFP is considerably smaller than the effect of persistent shocks (Panel A of Appendix Figure A.3). We do not find statistically significant differences between the passthrough of transitory shocks across the income distribution, although the quantitative impact is larger for workers in the fifth quintile than for workers in the first quintile (compare \$923 to \$285 in the case of a negative shock). These differences are mainly driven by differences in the annual earnings of each group rather than by the responsiveness of hourly wages to firm productivity shocks.

experience, have differing tenure-contingent contracts, or have accumulated specific human capital that is valuable for the firm and difficult to replace. In such cases, the firm may try to insure older and long-tenure workers from negative shocks more than younger or recently-hired workers. Alternatively, workers with longer tenure might receive a higher increase in earnings after a positive productivity shock, relative to a younger worker, if the firm implicitly "borrowed" from them (Michelacci and Quadrini, 2009). Our results are consistent with this intuition. As we show below, our estimates indicate that, relative to younger and short-tenure workers, older and long-tenure workers experience higher gains from persistent positive shocks and lower losses from persistent negative shocks to firms' productivity.

Panel C of Figure 4 shows the elasticity of wages to a persistent shock to firms' productivity for workers in different age groups. Three features of the figure are worth noticing. First, the passthrough from persistent positive shocks is weakly increasing with worker's age (line with circles). This implies that older workers get a higher wage increases than younger workers when firms receive a positive TFP shock, although the difference is not large. In contrast, the response of wages to a negative persistent TFP shock (line with squares) is larger than the response to positive shocks and decreases monotonically with workers' age. For instance, workers who are 56 years old or more lose 2.5% of their annual income in response to a one standard deviation negative shock, whereas workers who are between 15 and 25 years old lose 3.4% of their annual income on average.[37]

We then divide our sample of workers into five tenure groups: workers with a tenure equal to 2 years or less, a tenure between 3 and 4 years, between 5 and 7 years, between 8 and 14 years, and 15 years or more. Then, we run our baseline regression specification within each group while controlling for worker age. The results are shown in Panel D of Figure 4. We find that the passthrough from persistent TFP shocks to wages is hump-shaped in tenure. In fact, the effect of negative shocks is almost the same for newly hired workers as for workers who have been in the firm for more than 15 years. Workers in the middle of the tenure distribution, instead, appear to be much more exposed to negative firms shocks than the rest of the workers: when the shocks are negative, workers with medium tenure (between 5 and 7 years) lose the most, with a negative shock

[37] In contrast, we find that young workers gain more from a positive transitory shock and lose less after a negative shock than older workers (see Panel C of Appendix Figure A.3). More precisely, for workers who are 25 years old or younger, a negative (positive) transitory shock of one standard deviation translates into a decrease (increase) of \$370 (\$251) in annual earnings. For workers who are 56 years old or older, a negative (positive) shock of the same magnitude generates a decrease (increase) of \$604 (\$184) in annual earnings.

of one standard deviation generating a decline of $2,115 (3.4%) in their annual average income.

6.3 Aggregate State Dependence

Does the passthrough from idiosyncratic firms' shocks to workers' wages changes during recessions relative to expansions? This could be the case, if for example, a large aggregate economic shock, such as the Great Recession, decreases the workers' value of being unemployed (due to a reduction in vacancy postings).[38] This would lower workers' reservation wages giving firms greater ability to pass negative shocks on to their employees' wages. Similarly, a large negative aggregate shock may tighten credit constraints, and thus reduce firms' ability to insure their workers against negative idiosyncratic productivity shocks, inducing a higher passthrough.

To investigate whether passthrough is state-dependent, we estimate Equation (10) for two non-overlapping periods. The first considers observations from the two years of the Great Recession (2008 and 2009), whereas the second period considers all of the other (expansion) years in our sample. Our results, shown in columns (1) and (2) of Table II, indicate that the passthrough from positive firm shocks to worker wages is state-dependent, whereas the passthrough from negative shocks is not, and remains the same between recession and expansion periods.

To see this, first notice that during expansion years, the passthrough coefficients are quite similar to those obtained in our baseline analysis—compare column (4) in Table II to column (4) in Table I. This is not surprising, considering that most of the years in our analysis are expansionary years. Second, recession years show a different pattern, especially for the impact of persistent productivity shocks on wages. In particular, the passthrough from negative shocks remains almost unaltered between recessions and expansions (recall that the impact of a negative shock is given by $\beta_p^\eta + \beta_n^\eta$). In other words, firms that receive a negative idiosyncratic productive shock during a recession reduce the wages of their workers. In contrast, the passthrough from positive shocks collapses, becoming insignificant and almost zero, indicating that firms that received a positive productivity shock do not, on average, pass that increase on to their workers. The passthrough from transitory shocks, on the other hand, does not show significant variation over the business cycle. In conclusion, our results suggest that recessions are neither periods in which firms are unable to cut wages when facing an idiosyncratic negative shock, nor periods with a higher passthrough from

[38] Similar to the rest of the world, Denmark was hit by a severe economic downturn in 2008. Between 2007 and 2009, the GDP of Denmark declined around 7.0%, while the unemployment rate rose by 2.0 percentage points.

Table II – Passthrough in Recessions and for Switchers

Specification:	(1) Expansions	(2) Recessions	(3) Switchers
η_{jt}	.056***	.014	.025***
	(.004)	(.032)	(.007)
$\eta_{jt} \times \mathbb{I}_{\eta_{jt}<0}$	.080***	.127***	.002
	(.007)	(.041)	(.002)
ϵ_{jt}	.025***	.032***	.057***
	(.006)	(.008)	(.010)
$\epsilon_{jt} \times \mathbb{I}_{\epsilon_{jt}<0}$	.021**	−.007***	−.018
	(.009)	(.018)	(.018)
$Mills_{it}$	−.230***	−.333***	−.012***
	(.020)	(.035)	(.003)
R^2	.81	.44	.70
Obs. (Millions)	4.2	1.1	0.55
Monetary Value of a Shock to Firm TFP (US$ 2010)			
$\eta_{jt} > 0$	$638	$167	$2,099
$\eta_{jt} < 0$	$1,528	$1,662	$1,914
$\epsilon_{jt} > 0$	$252	$336	$554
$\epsilon_{jt} < 0$	$453	$269	$369

Table II shows a set of OLS panel regressions controlling for firm and worker characteristics. In column (1), expansion years are all years in our sample with the exception of 02/03 and 08/09. Results for 08/09 are displayed in column (2). Column (3) shows the estimated passthrough elasticities for switchers relative to the unanticipated change in TFP resulting from the change in firm. $*p < 0.1, **p < 0.05, ***p < 0.01$. Robust standard errors are clustered at the firm-level.

negative shocks. Rather, firms do not increase wages when facing a positive idiosyncratic shock.[39]

7 Switchers

The results of the previous sections have focused on the effect of TFP shocks on stayers, that is, workers who maintain a stable employment relationship with a firm for the years over which the change in TFP is calculated. This is a natural starting point, as changes in wages for stayers can be more easily tied to changes in firm productivity. In this section we shift our focus to those individuals who change employers between two consecutive years, or "switchers".[40] Firm shocks can be passed through to these workers in two ways. First, as we discuss in Section 4.3, productivity shocks are an important determinant of employment risk and job mobility. Second,

[39]Our results are consistent with those presented by Grigsby *et al.* (2019) that show that during the Great Recession, the probability of US workers of receiving a (nominal) wage cut increased whereas the probability of receiving a wage increase fell sharply.

[40]We define switchers as those workers who change primary employers between two consecutive years. For workers with multiple jobs in a year, we define the primary employer as the firm that provides the higher income within a year. Our data does not allow us to cleanly distinguish whether an individual passed through an unemployment spell prior to joining a different employer or had a direct transition between employers. Around 20% of workers in our sample change primary employers in any given year.

the wage change which results from this employment change may depend on the productivity level and growth at both the source and destination firm. We examine both of these passthrough channels in this section.

To investigate how firm shocks affect employment risk, we use a linear probability model similar to Equation (7) to calculate the probability of switching within 33 bins of the TFP growth distribution, conditional on worker and firm characteristics. The results are shown in Table A.6. As implied by the probit regression from Section 4.3, changes in firm TFP are a significant driver of worker mobility. Workers employed in firms that experience a negative change in productivity of 45 log points or more are 4 times more likely to separate from their firm than workers employed in firms that experience a decline in productivity of 30 log points who are in turn twice as likely to separate as those in firms with 15 log point declines.

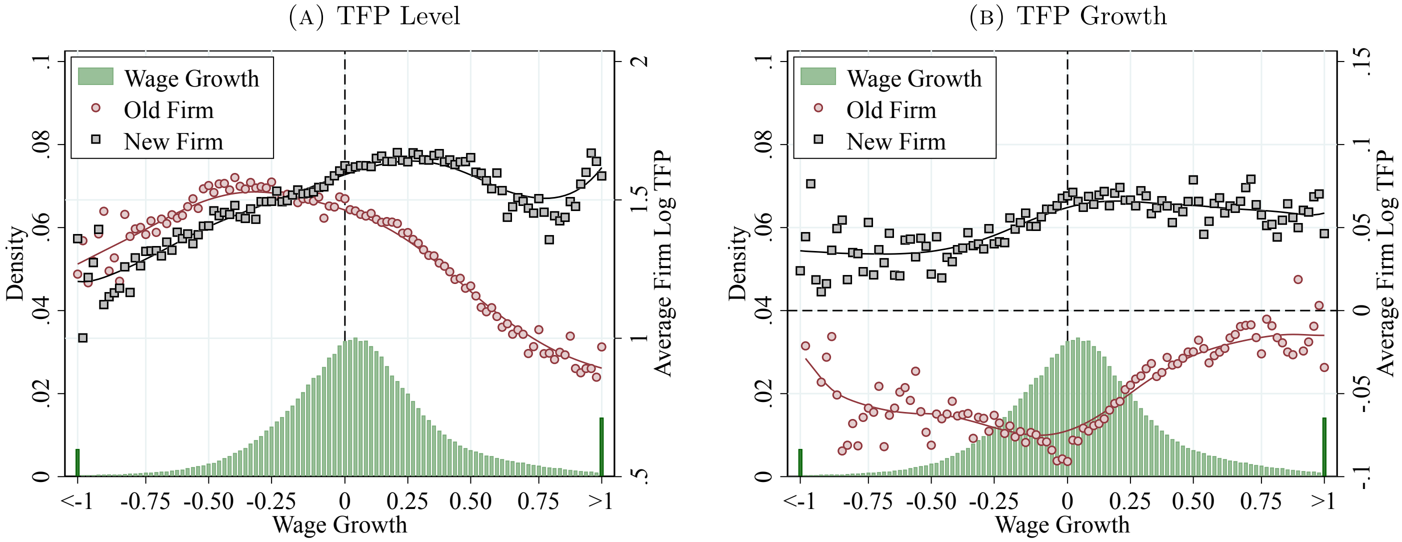
Workers who switch jobs also experience larger income changes than workers than stay in the same job. This difference can be explained, in part, by the fact that switchers are transitioning between firms of (often significantly) different productivity levels.[41] To see this, in Panel A of Figure 5, we sort switchers into bins by their log hourly wage growth and plot the average log TFP of their old and new firms. Each red circle in Figure 5 is the average log TFP of the firms *out of which* workers of a given wage growth percentile switched, while each black square is the average log TFP of the destination firms *into which* workers of the corresponding wage growth percentile switched. Two patterns are worth noticing. First, the difference in firm productivity between positive and negative wage changes is striking. Workers who experience a reduction in hourly wages of between 25 and 75 log points when they switch firms have moved, on average, to firms that are 10 log points less productive. In contrast, workers who experience an increase in hourly wages of 25 log points have moved to a firm that is on average 25 log points more productive. This difference in productivity increases as workers experience larger wage gains. There is also a group of workers who, despite experiencing a wage cut of between 0 to 20 log points, have moved to firms with greater average productivity, perhaps motivated by prospects of higher future wage growth.[42]

A second noticeable pattern in Panel A of Figure 5 is that workers experiencing larger wage

[41] Appendix Figure A.4 shows that the dispersion in (and average) residual hourly wage growth is higher for switchers than for stayers.

[42] We find similar patterns when looking at different percentiles of the distribution of the log TFP (Figure A.5 in Appendix A). In particular, the higher average productivity of switchers' new firms is not driven by a handful of highly productive firms that are offering higher wages, but rather the productivity distribution of destination firms is shifted to the right.

Figure 5 – Log Hourly Wage Growth For Switchers and Firm TFP



Note: Figure 5 is based on a pooled sample switchers and their corresponding firms. The green bars show the share of switchers within different bins of the log hourly wage growth distribution (left y-axis). To construct the graph, we partition the wage growth distribution into 101 equally-spaced bins between -1 and 1. The left- and right-most bins encompass the remaining left and right tails of the distribution. In Panel A (Panel B) the red dots show the average log TFP (average log TFP growth) of the firms that employed the workers in the corresponding wage change bin in period $t-1$. The black squares show the average TFP (average log TFP growth) for the firms that employed the workers in each bin in period t.

gains from switching firms are not moving, on average, to firms with higher productivity, relative to workers with smaller, but still positive, wage gains. Instead, workers with larger wage gains tend to be those switching out from relatively low productivity firms. Workers whose log hourly wages increase by 50 log points are switching on average into firms with the same productivity as workers who gain 10 log points in hourly wages, but the former are switching out from firms that are 25 log points less productive.

Interestingly, workers move on average to firms with positive TFP *growth,* independently of whether the hourly wage growth is positive or negative. Panel B of Figure 5 plots, for the same wage growth bins, the average TFP growth for switchers' old and new firms. Notably, the average switcher in every bin of the wage growth distribution is moving from a firm with negative productivity growth into a firm with positive productivity growth. This is consistent with standard job ladders models (Burdett and Mortensen, 1998) which predict that workers move from low- to high-productivity firms over time.

Regression Results

To obtain quantitative estimates of the between-firm passthrough elasticity, we run a set of panel regressions similar to the baseline model we consider in our stayers sample. Notice that the interpretation of a productivity shock is different for switchers than for stayers. For stayers, it represents an *unanticipated* change in productivity in the firm in which they work, whereas for switchers, we define a TFP shock as the *unanticipated* difference in productivity between two different firms.[43] Hence, a positive TFP change for a switcher implies that the worker moved to a firm with higher realized TFP relative to the *expected* TFP of the firm at which the worker used to work.

To capture these differences, we modify our baseline specification to include the shocks to the productivity of both of the firms between which the individual is transitioning . In particular, we estimate

$$\begin{aligned}\Delta\hat{w}_{ijkt} = {} & \alpha + \beta_p^{\eta}\eta_{jkt} + \beta_n^{\eta}\eta_{jkt} \times \mathbb{I}_{\eta_{jkt}<0} + \beta_p^{\varepsilon}\varepsilon_{jkt} + \beta_n^{\varepsilon}\varepsilon_{jkt} \times \mathbb{I}_{\varepsilon_{jkt}<0} \\ & + Z_{jt}\Gamma_1 + Z_{kt}\Gamma_2 + X_{it}\Lambda + \rho\tilde{\lambda}_{ijt} + \delta_t + \zeta_{ijkt},\end{aligned}$$

where $\Delta\hat{w}_{ijkt}$ is the change in the ability-adjusted real log hourly wages of an individual who moved from firm k to firm j. In this case, η_{jkt} is the unanticipated difference in the persistent component of TFP between the old and new firms, defined by $\eta_{jkt} = \omega_{jt} - \mathbb{E}[\omega_{kt}|\omega_{kt-1}]$, whereas ε_{jkt} is the transitory shock at the new firm. The matrices Z_{jt} and Z_{kt} include firm $j's$ and $k's$ characteristics such as size, age, and lag productivity.[44]

Column (3) of Table II shows the results of this analysis. Notice that the elasticity of switchers' wages to firms' TFP shocks is smaller than for stayers (compare to column (4) in Table I), but the dollar value of the shock is much larger for switchers (bottom panel of Table II). The large difference in the dollar values between switchers and stayers stems from the differences in the dispersion of TFP changes, as well as differences in the average wage. For example, the elasticity of wage growth to a persistent negative TFP shock is much larger for stayers than for switchers (0.131 versus 0.027). However, the average wage loss from a one standard deviation within-firm negative TFP shock is smaller than the loss from a persistent one standard deviation firm-to-firm drop in TFP (compare \$1,495 versus \$1,914, or 2.5% versus 3.4% of average annual income). One additional remarkable difference with respect to stayers is that the passthrough for switchers is *symmetric* (the coefficient of $\eta_{jt} \times \mathbb{I}_{\eta_{jt}<0}$ is effectively 0). This implies that workers climbing up the productivity ladder face similar wage changes as those making equal movements down the ladder.

[43] In both cases, the unanticipated change is defined relative to the expected productivity of their origin firm: $\mathbb{E}[\omega_{kt}|\omega_{kt-1}]$.

[44] We control for selection in this regression by including the inverse Mills ratio $\tilde{\lambda}_{ijt}$ which is estimated from a first-stage model similar to Equation (7), with the exception that D_{ijt} is instead an indicator that equals 1 if the worker moved to a different firm in period t.

8 Implications for the Labor Supply Elasticity

Our estimates of the passthrough elasticity can also give us intuition about the underlying labor supply curve. To see this, recall that the passthrough elasticity can be written as $\epsilon_A^w = \epsilon_A^L / \epsilon_w^L$ where ϵ_A^L is the elasticity of labor with respect to firm productivity, and ϵ_w^L is the labor supply elasticity (see Equation 4). Rearranging this, we can define the labor supply elasticity as the ratio of the labor demand elasticity ϵ_A^L and the passthrough elasticity: $\epsilon_w^L = \epsilon_A^L / \epsilon_A^w$. A standard modeling assumption in many contexts has been that labor markets are perfectly competitive, implying an infinite labor supply elasticity and a passthrough elasticity of zero. More recently, a growing literature has attempted to obtain empirical estimates of these labor supply elasticities, often finding very low elasticities (see Manning (2011) and Card *et al.* (2018)).[45]

The main difficulty in identifying the labor supply elasticity is finding exogenous variation in wages. Although estimating the labor supply elasticity is not the primary purpose of this paper, our framework and data do provide several advantages we can leverage. In particular, given our exogenous measures of firm productivity, it is straightforward to extend the analysis to obtain estimates of the elasticity of labor with respect to productivity $\left(\epsilon_A^L\right)$, which we can then use along with the passthrough elasticity estimates $\left(\epsilon_A^w\right)$ to back out the labor supply elasticity. To do this, we estimate the following firm-level regression,

$$\Delta a_{jt} = \alpha + \beta_a^{\nu} \Delta \nu_{jt} + Z_{jt}\Gamma + \delta_t + \zeta_{jt}^f,$$

where $a_{jt} = \log A_{jt}$ is the log of the firm's total ability-adjusted labor input, ν_{jt} is log TFP, and Z_{jt} is a vector of firm characteristics including the firm-level ability price (ψ_{jt}). We weight this firm-level regression by (lagged) total ability-adjusted employment so that it corresponds to our individual-level estimates of Equation (8). Our parameter of interest is β_a^{ν} which gives us an estimate of the elasticity of labor with respect to productivity, ϵ_A^L.

Our results—displayed in Appendix Table A.6—give us a precisely estimated elasticity of $\hat{\beta}_a^{\nu} = 0.43$, which means that a 1% increase in productivity on average leads to a 0.43% increase in (ability-adjusted) labor. We can combine this with our baseline passthrough elasticity estimate

[45] For example, Dube *et al.* (2020) attempt to measure the elasticity directly using data from Mechanical Turk and find an implied elasticity of around 0.1. Azar *et al.* (2019) use application data from CareerBuilder.com to estimate a model of demand for job vacancies and recover (somewhat more reasonable) labor supply elasticities of around 5.

from Table I, which was 0.076. Together, these results provide us with an implied average labor supply elasticity of $0.43/0.076 = 5.66$, which is very similar to the results obtained by Azar *et al.* (2019) despite using very different methods and data. A labor supply elasticity of 5.66 suggests (through the lens of our simple monopsony model) an average wage markdown of 15%, which means that firms do seem to have substantial labor market power.

9 Conclusions

In this paper, we present new evidence on the passthrough from firms' productivity shocks on workers' wages. We show that the passthrough elasticity—defined as the percentage variation in hourly wages generated by a percentage change in firms' productivity—is not only economically and statistically significant, but also markedly asymmetric, in that a negative shock to firm productivity generates a much larger decline in wages, relative to the gain in wages from a positive shock to firm productivity of the same magnitude. We also find substantial variation across several key dimensions of worker and firm heterogeneity. Taken together, our results suggest an important role for firms' TFP shocks in accounting for workers' income variability.

Our analysis is based on high-quality employer-employee matched administrative panel data from Denmark that we use to address several important issues that have been overlooked by the empirical literature: the endogeneity of firm output and input choices, the effect worker mobility, and the impact of changes in firm-level productivity for workers who switch between firms. To accomplish this, we provide a more direct measure of firms' total factor productivity which controls for labor quality and we exploit the employment and income information of workers' spouses. We find that controlling for selection has a significant impact on the estimated passthrough from firms' TFP shocks to workers' wages.

Our analysis offers insights into how movements up and down the firm productivity ladder affect wages for workers who switch employers. In particular, we show that switchers who obtain larger wage gains are moving up from relatively lower rungs on the ladder than workers who obtain smaller wage gains, rather than moving to higher rungs on the ladder. Interestingly, we find that workers who switch employers are (on average) moving from firms with negative productivity growth to firms with positive productivity growth, regardless of whether they face wage gains or losses. Unlike passthrough for incumbent workers, movements between firms up and down the productivity ladder generates symmetric passthrough from productivity to wages.

We show that our findings can be rationalized in a model in which firms have labor market power and compete strategically. Our model predicts positive passthrough and a selection bias problem, both of which we confirm in the data. Under standard parameter choices, our model also predicts the negative asymmetric passthrough which declines in productivity and firm market share that we find in the data. This suggests that accounting for strategic interaction and market power is critical for any theory seeking to account for these salient features of wage dynamics and the labor market. Through the lens of the model, we calculate that firms have significant market power and tend to pay workers substantially below their marginal productivity.

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Supplemental Online Appendix

NOT FOR PUBLICATION

Appendix

A Additional Tables and Figures

Table A.1 – Summary Statistics

	2000	2005	2010		2000	2005	2010
Panel A: Workers				Panel B: Firms			
Obs. (000s)	469.9	653.3	625.2	Obs. (000s)	29.6	45.2	48.3
% Women	28.0	30.0	31.0				
% High School	33.7	29.6	27.4	Firm Age: % Share of Firms			
				<5	8.9	10.9	11.4
% Age groups				5-10	23.5	44.3	48.5
Below 25	8.69	6.7	8.1	10+	67.6	44.9	40.1
25-35	30.6	26.7	21.4				
36-45	27.0	30.9	31.4	Firm Age: % Share of Employment			
46-55	23.3	22.3	25.4	<5	6.2	6.3	5.0
Above 55	10.3	13.4	14.0	5-10	35.7	33.9	34.9
				10+	58.2	59.9	60.1
Annual Labor Earnings							
Mean	49,513	53,104	54,176	Firm Size: % Share of Firms			
P10	34,544	35,954	35,954	20	83.0	84.1	87.4
P50	48,533	51,534	52,052	20-100	13.9	13.1	10.4
P90	77,653	83,283	87,553	100+	3.1	2.7	2.3
Hourly Wages				Firm: Size: % Share of Employment			
Mean	30.35	32.23	32.88	20	24.3	25.5	28.2
P10	20.97	21.82	21.82	20-100	28.1	28.8	26.6
P50	29.46	31.59	31.91	100-1000	36.7	35.2	33.3
P90	47.13	50.55	53.14	1000+	10.8	10.5	11.8

Table A.1 shows different statistics for workers and firms in our baseline sample. All monetary values are converted to US dollars of 2010. To avoid the disclosure of any sensitive information, for all percentiles, we report the mean of all observations *within* a percentile-band rather than individual observations at the percentile cutoff.

Table A.2 – First-Stage Probit Estimates for Selection Model

Variable	Pr(Staying in Firm)	
	(1) Productivity Growth, $\Delta\nu_{jt}$	(2) Persistent Shock, η_{jt}
$\Delta\nu_{jt}$	.028*** (.005)	
$\Delta\nu_{jt} \times \mathbb{I}_{\Delta\nu_{jt}<0}$	.977*** (.004)	
η_{jt}		.313*** (.006)
$\eta_{jt} \times \mathbb{I}_{\eta_{jt}<0}$		1.111*** (.004)
Age	-.003*** (.001)	-.004*** (.001)
Male	-.132*** (.002)	-.154*** (.002)
Lag Tenure	.040*** (.000)	.040*** (.000)
Married	.027*** (.003)	.026*** (.003)
Change Spouse	-.119*** (.011)	-.119*** (.012)
Spouse's Firm's TFP (ν_{jt})	.017*** (.004)	.011*** (.004)
Spouse Stayer	.028*** (.003)	.026*** (.003)
Obs. (Millions)	7.04	7.04

Notes: Table A.2 shows a few selected parameter estimates from our first-stage probit model. $*p < 0.1, **p < 0.05, ***p < 0.01$. Robust standard errors are clustered at the firm-level.

Table A.3 – Moments of the Distribution of Firm Productivity

Estimation	Std. Deviation	Skewness	Kurtosis	P90-P10	P75-P25
Log-TFP (ν_{jt})					
Ability Adjusted	0.63	1.36	6.75	1.17	0.67
Labor Hours	1.57	-1.82	11.40	3.55	1.75
TFP Shocks (η_{jt})					
Ability Adjusted	0.20	5.59	165	0.28	0.13
Labor Hours	0.64	0.50	34.6	1.10	0.43

Note: Table A.3 shows selected moments for productivity in levels (ν_{jt}) and persistent shocks to productivity (η_{jt}) estimated using both our ability adjusted measure of labor inputs and the standard method of using total hours worked at the firm as the labor input.

Table A.4 – Moments of the Ability-Adjusted Firm Productivity Distribution

		(1)	(2)	(3)	(4)	(5)	(6)
		$TFP_{j,t}$	$\Delta^1 TFP$	$\Delta^3 TFP$	$\omega_{j,t}$	$\eta_{j,t}$	$\epsilon_{j,t}$
Mean	μ	0.0	0.02	0.01	0.0	0.0	0.0
Std. Dev.	σ	0.63	0.26	0.32	0.55	0.20	0.31
Skewness	γ	1.36	-0.28	-0.30	1.48	5.59	0.98
Kurtorisis	κ	6.75	18.44	13.41	7.23	165.0	11.43
Auto Corr.	ρ	0.92	-0.32	0.38	0.94	-0.20	0.66
Percentiles							
P1		-1.33	-1.11	-1.30	-1.08	-0.71	-0.93
P5		-0.81	-0.40	-0.49	-0.66	-0.22	-0.42
P10		-0.40	-0.25	-0.32	-0.54	-0.14	-0.30
P50		-0.12	0.0	0.01	-0.13	-0.01	-0.2
P90		0.77	0.24	0.32	0.68	0.14	0.32
P95		1.15	0.34	0.45	1.01	0.20	0.47
P99		1.91	0.61	0.75	1.69	0.37	0.76
P90-P10		1.17	0.49	0.64	1.22	0.28	0.62
KSK		0.52	-0.04	-0.03	0.32	0.07	0.67
Obs	N	673K	546K	446K	673K	673K	673K

Note: Table A.4 shows moments of the estimated distribution of firm's productivity and productivity growth.

Table A.5 – Summary Statistics for Hourly Wage and Productivity Shocks

	Panel A: Workers		Panel B: Workers			Panel C: Firms		
	Δw_{ijt}		$\Delta \nu_{jt}$	η_j	ϵ_{jt}	$\Delta \nu_{jt}$	η_j	ϵ_{jt}
	Stayers	Switchers	Stayers					
Mean	0.02	0.07	0.00	0.02	0.01	0.00	0.00	0.00
Std. Dev.	0.18	0.36	0.26	0.27	0.20	0.24	0.19	0.17
P10	-0.14	-0.30	-0.25	-0.27	-0.16	-0.23	-0.16	-0.17
P25	-0.05	-0.11	-0.12	-0.13	-0.07	-0.10	-0.08	-0.08
P50	0.01	0.06	0.00	0.00	0.01	0.00	0.00	0.00
P75	0.08	0.23	0.12	0.14	0.09	0.10	0.07	0.08
P90	0.18	0.46	0.26	0.34	0.18	0.22	0.19	0.17
Obs. (Millions)	6.47	0.56	6.47	6.47	6.47	0.57	0.57	0.57

Table A.5 shows the sample statistics for workers' log hourly wage growth (Panel A) and firms' productivity shocks (Panel B at the worker-level and Panel C at the firm-level). To avoid the disclosure of any sensitive information, for all percentiles, we report the mean of all observations *within* a percentile-band rather than individual observations at the percentile cutoff.

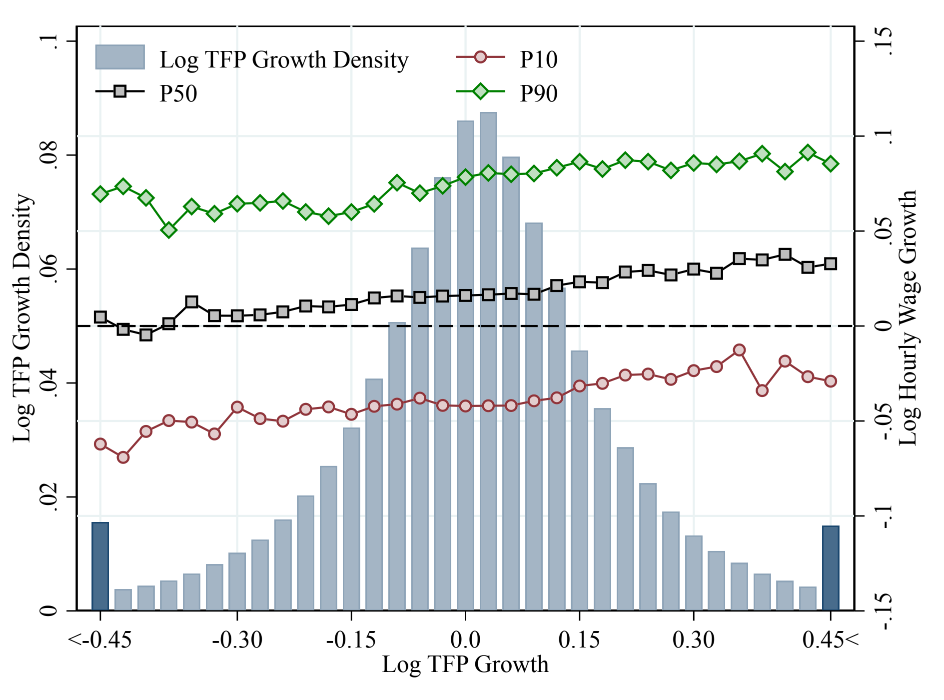
Table A.6 – Elasticity of Labor with respect to Productivity

	(1)	(2)
	Δa_{jt}	Δa_{jt}
β_a^{ν}	.72***	.43***
	(.032)	(.027)
Controls	No	Yes
R^2	.30	.76
Obs. (Millions)	.47	.47
Labor Supply Elasticity	9.47	5.66

Table A.6 shows two OLS panel regressions with and without controlling for firm characteristics. a_{jt} is log total ability-adjusted labor. ν_{jt} is the log of total firm TFP. Firm controls include lags of firm age, TFP, ability-price (wage), and employment. $*p < 0.1, **p < 0.05, ***p < 0.01$. We report the robust standard errors in parentheses. The implied labor supply elasticity is calculated by dividing β_a^{ν} by the passthrough elasticity estimate from column 1 of Table I (0.076).

Figure A.1 – Wage Change Percentiles Across the TFP Change Distribution

(A) Hourly Wages



(B) Adjusted Hourly Wages

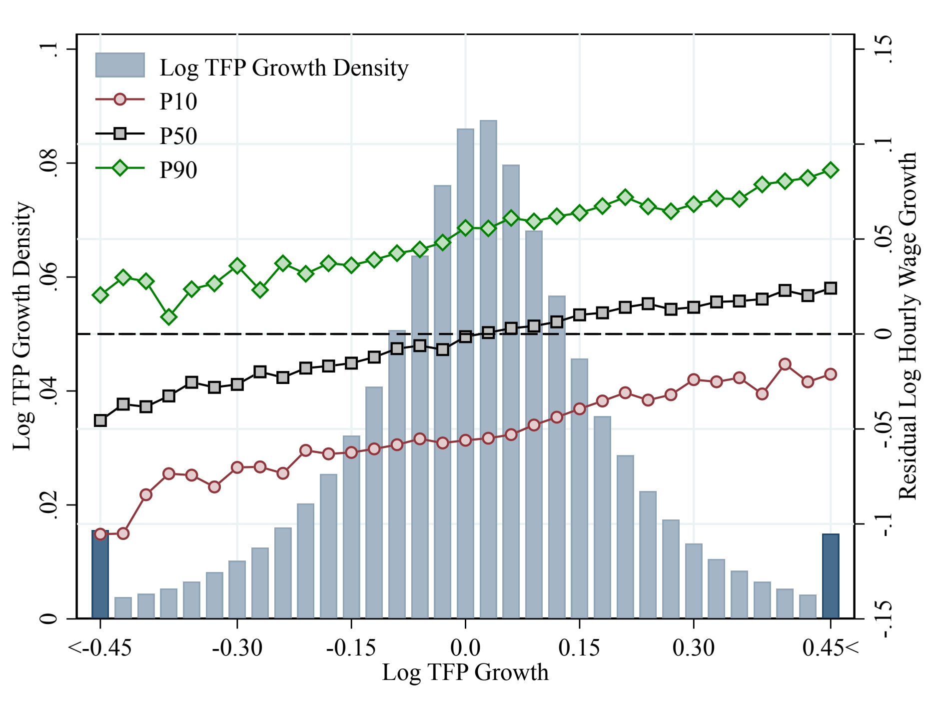
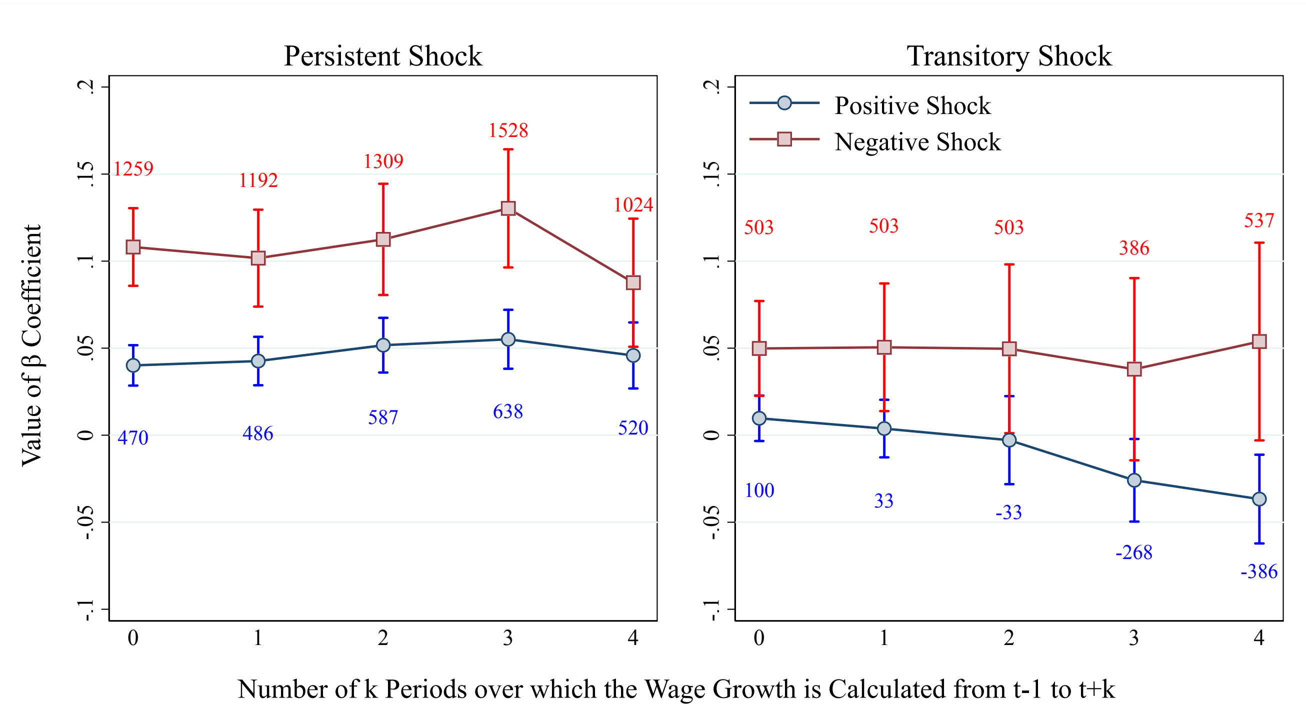


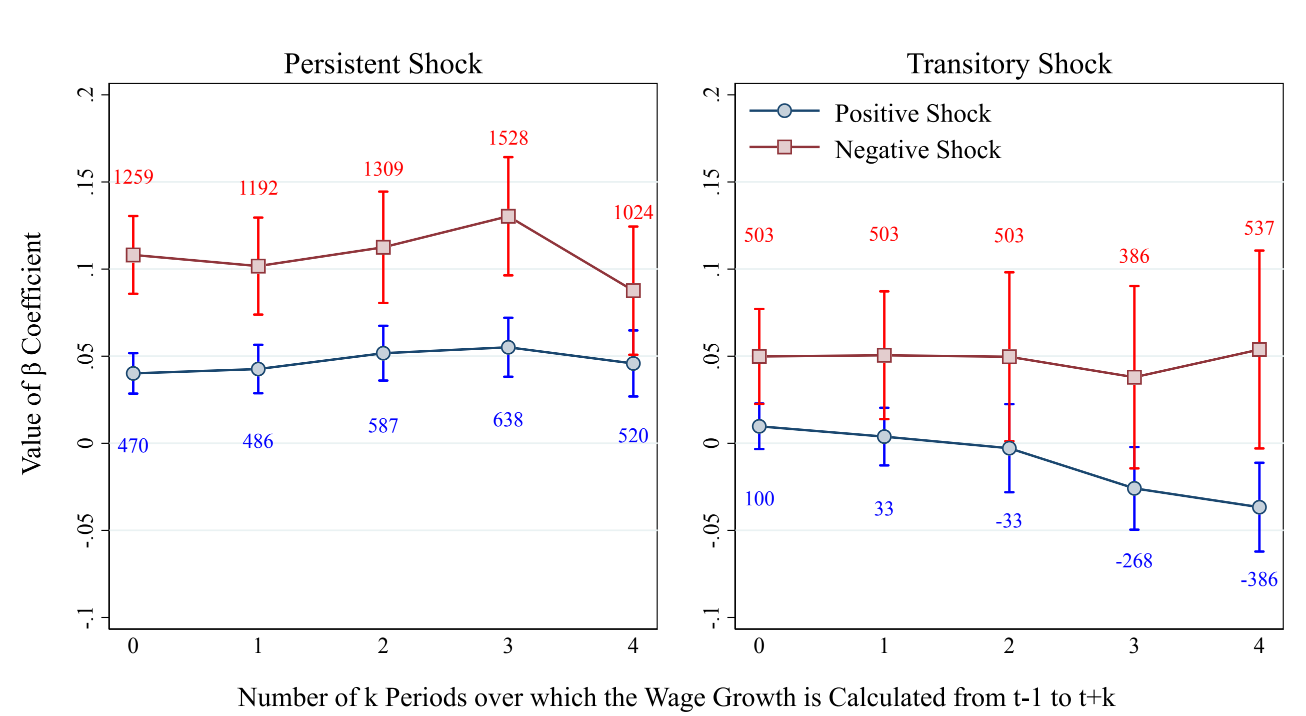
Figure A.1 is based on a pooled sample of firms and workers between the years 1996 to 2010. The blue bars show the share of firms within different bins of the log TFP growth distribution (plotted on the left y-axis). To construct the plot we separate firms into 41 equally sized bins between -.45 and 45. The left- and right-most bins, marked in darker blue, contain the remaining left and right tails of the distribution, and thus are not the same size as the other bins. The right axis of each panel shows the within-percentiles means of the hourly wage growth (top panel) and hourly wage growth after controlling for worker characteristics, firm characteristics, and endogenous selection as explained in Section 4.3 (bottom panel). Hourly wage growth measures are calculated for a sample of stayers defined as workers for whom the firm providing the higher total annual earnings was the same in periods t and $t-1$. To avoid disclosure of any sensitive information, we report the mean of all observations *within* a percentile-band rather than individual observations at the percentile cutoff.

Figure A.2 – Positive and Negative Shocks Have a Long-Lived Impact on Wages

(a) Positive and Negative Shocks

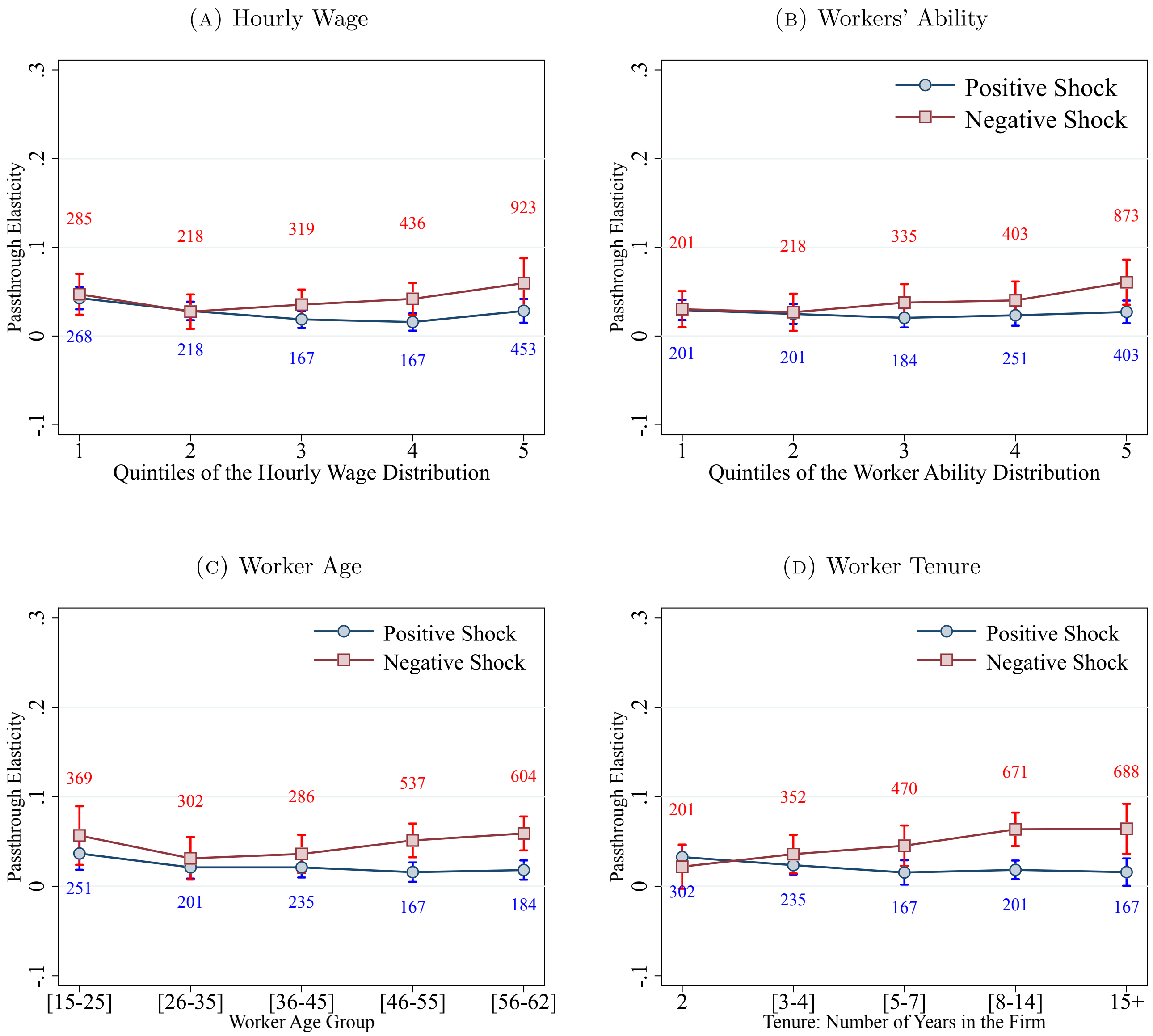


(b) Positive and Negative shocks for a Balanced Panel of Workers



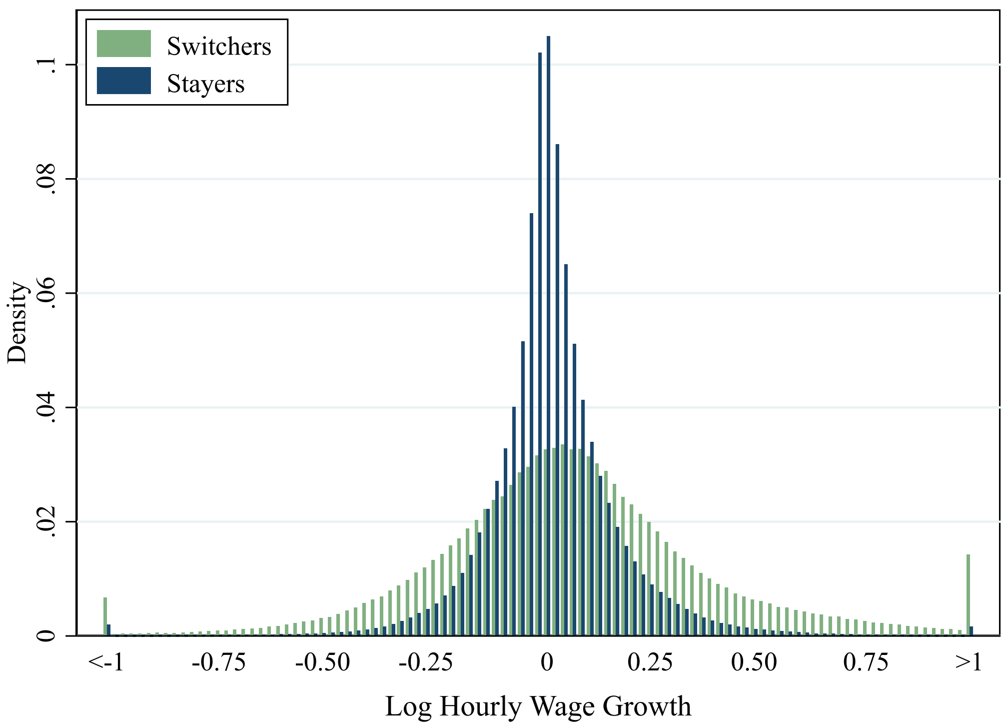
Note: Figure A.2 shows the elasticity of hourly wages to firm productivity. In each plot, hourly wage growth is measured as the change between year t and $t+k$ where k is plotted on the x-axis. Firms' productivity shocks are measured by η_{jt} (left panel) and ϵ_{jt} (right panel). In each plot, the points shows the passthrough elasticity coefficient (β) from a separate second-stage regression, while the vertical lines show 95% confidence intervals around those point estimates. In each plot, the numbers above and below the lines represent the monetary value of a shock of one standard deviation calculated using the corresponding elasticity. All monetary values (in 2010 US$) are calculated relative to the average annual labor earnings within the corresponding group.

Figure A.3 – Worker Heterogeneity: Passthrough from Transitory Firm TFP Shocks



Note: Panel A of Figure A.3 shows the elasticity of hourly wages to a persistent (left panel) and transitory (right panel) productivity shock for workers within different age groups. Panel B shows the same statistics for workers within different tenure groups. Tenure is measured as the number of years for which the worker has been employed at that firm. Tenure bins are chosen so as to have groups of roughly similar size.

Figure A.4 – Log Hourly Wage Growth For Switchers and Stayers



Note: Figure A.4 is based on a pooled sample of stayers and switchers (workers who move across firms between firms $t-1$ and t) and their corresponding firms. In the top panel, the green bars (blue bars) show the share of switchers (stayers) within different bins of the hourly wage growth distribution (left y-axis). To construct the graph we partition the wage growth distribution into 101 equally-spaced bins between -1 and 1. The left- and right-most bins encompass the remaining left and right tails of the distribution, and thus are not the same size as the other bins.

Figure A.5 – Hourly Wage Growth for Switchers and Firm Productivity

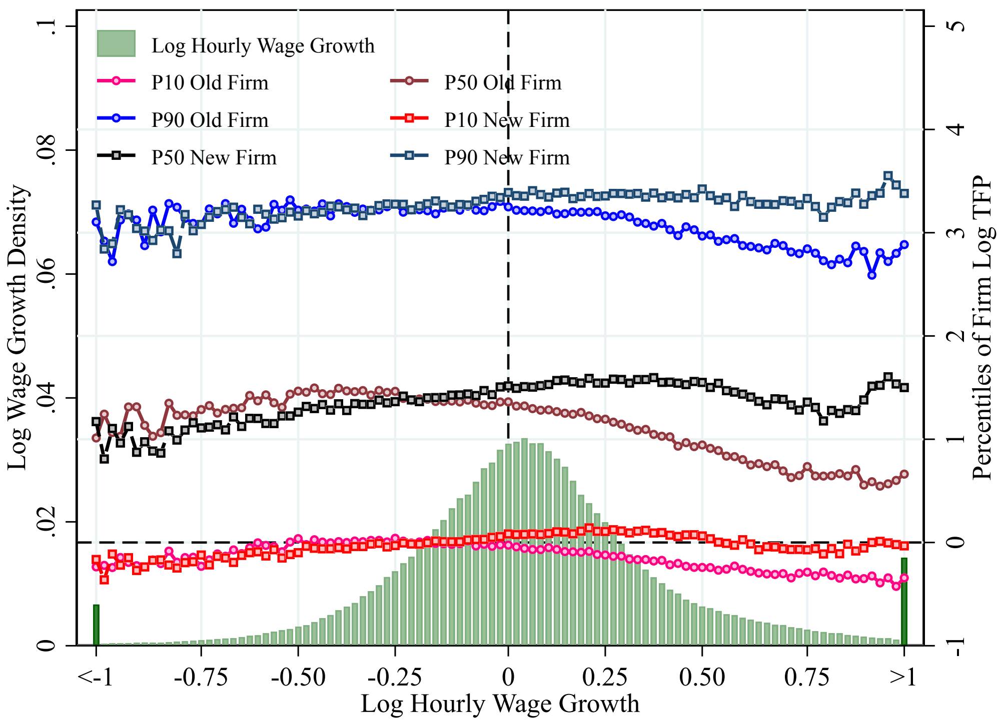


Figure A.5 is based on a pooled sample of switchers (workers who move across firms between firms $t-1$ and t) and their corresponding firms. The green bars show the share of workers within different bins of the hourly wage growth distribution (left y-axis). To construct the graph we partition the wage growth distribution into 101 equally spaced bins between -1 and 1. The left and right-most bins, marked in darker green, encompass the remaining left and right tails of the distribution, and thus are not the same size as the other bins. The circles show percentiles of the log TFP distribution for the firms that employed the workers in period $t-1$; The squares show percentiles of the log TFP distribution for the firms that employed the workers in period t. To avoid disclosure of any sensitive information, we report the mean of all observations *within* a percentile-band rather than individual observations at the percentile cutoff.

Figure A.6 – Conditional Probability of Switching

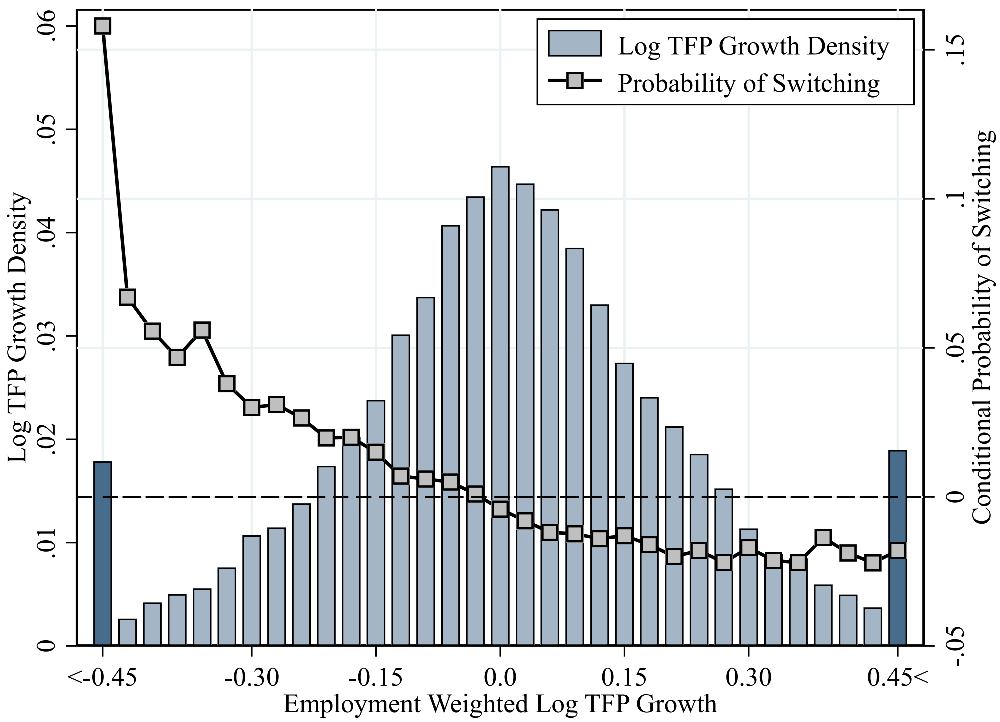
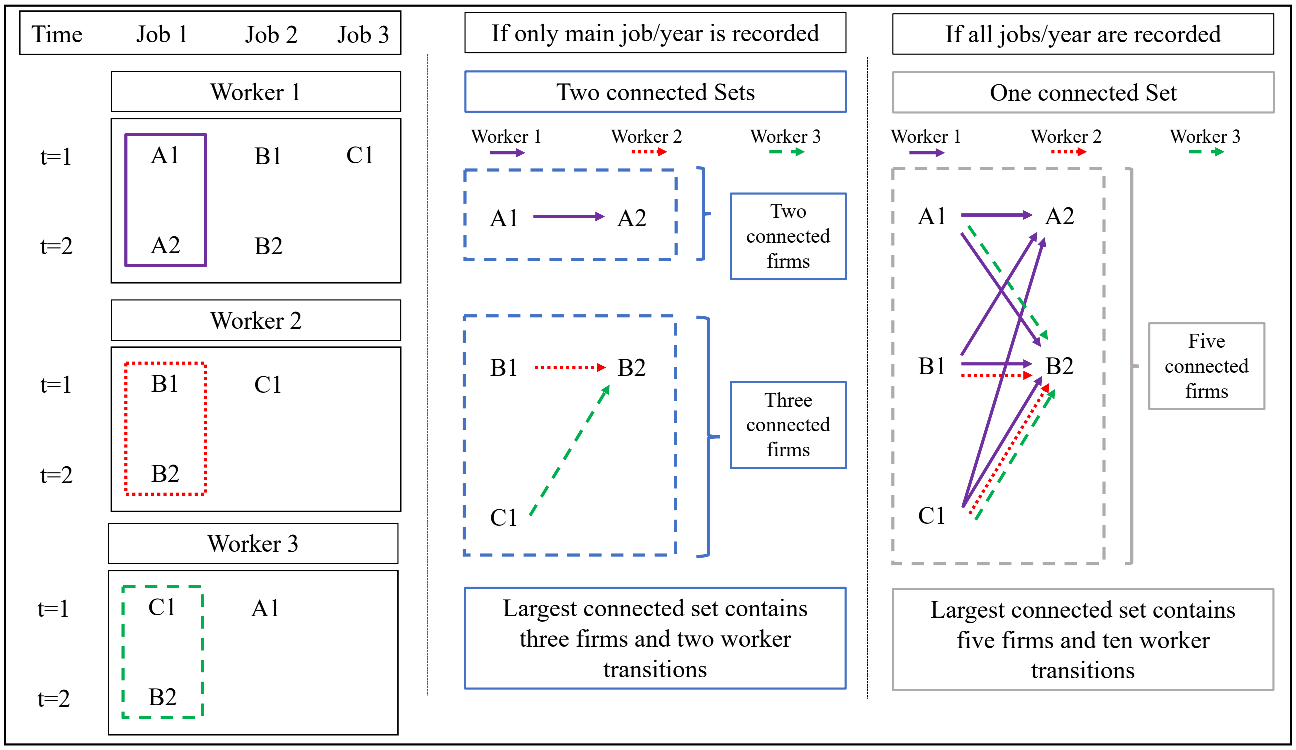


Figure A.6 shows the average conditional switching probability within each bin of the firms' log TFP grow distribution ($\Delta\nu_{jt}$). The conditional probability is obtained from a linear probability model similar to the model used to estimate the inverse Mills ratio. See Section (4.3) for additional details.

Figure A.7 – Connected Sets using Multiple Jobs



Note: Figure A.7 shows how we identify the parameters of the two-way fixed effect model with firm-year fixed effects and multiple jobs per worker-year.

B Identification in an AKM Framework with Time Varying Fixed Effects

In this appendix, we discuss the identification of the parameters in our model of wages with two sided fixed effects and time-varying firm characteristics. Recall the model of wages we use is given by:

$$w_{ijt} = \alpha_i + X_{it}\Gamma_t + \psi_{j(i,t)t} + \xi_{ijt}.$$

The identification of the parameters of this model can be separated into three parts: the time-varying covariate coefficients, the individual fixed effects, and the time-varying firm effects.

Figure A.7 provides a graphical representation of how we construct the connected set in our model with firm-time fixed effects and multiple observations per worker within a year. The left panel shows a theoretical set of jobs across two years for three different workers. In this example, worker 1 has three jobs in period 1, working at firms A, B, and C. In period 2, worker 1 has only two jobs—working at firms A and B—and so on. Workers' main jobs—those that provide the largest income in a year—are identified by solid purple, dotted red, and dashed green boxes. Because we estimate firm effects separately for each year, we treat each firm-year observation as a separate firm. Thus, A1 and A2 refer to firm A in periods 1 and 2, respectively.

The middle panel shows the network graph of all 5 firm-year nodes if we were to consider only each worker's primary job (as is typically done in the literature). For example, worker 1 moves from A1 in period 1 to A2 in period 2, while worker 3 moves from C1 to B2. The result is two connected sets; the first, with firms A1 and A2, and the second (the largest connected set) with firms B1, B2 and C1. Each firm is connected to the rest of the set with just a single worker transition.

The right panel of Figure A.7 shows the network graph when we consider all of the worker-firm pair information available in a year. In this case, each first-period job worked by an individual is connected to every second-period job worked by that same individual. For example, worker 1 is employed in firms A1, B1, and C1, in period 1, and A2, and B2 in period two, leading to a full set of connections between period 1 and period 2 firms as depicted by the multiple solid lines in the right panel of Figure A.7. This leads to a connected set including all 5 firms in the sample. Moreover, each firm in this larger connected set is connected by at least 3 worker transitions to the rest of the set, strengthening the identification of the firm and worker fixed effects.

One important concern about our setting—which is common to all AKM fixed effect regressions—is that there may be many firm-time pairs that are weakly connected to the largest connected set. For example, in our data set, we find that roughly 5.2% of all firm-time observations have only one transition connecting these firms to the largest connected set, with another 13.3% of firm-time observations having only two connections. As noted by Andrews *et al.* (2008), if firm fixed effects are identified using a small number of workers who move across firms, the AKM estimates may be biased, overstating the role of firms relative to the role of sorting in accounting for the variation in labor earnings. Notice, however, that using multiple job observations for workers helps to reduce the extent of this limited mobility bias: if we include only one job per worker, we find that 7.0% of firm-time observations have only one link (versus 5.2% in our baseline sample), and 20.1% have only two links to the largest connected set (versus 13.3% using workers' top three job connections). Furthermore, the limited mobility bias only affects our inference about the importance of firms and sorting in accounting for wage dispersion (the $\psi_{j(i,t)t}$ component), but not the component of the hourly wages accounted for by worker heterogeneity (as measured by $\alpha_i + X_{it}\Gamma_t$), which is crucial for the method we use to estimate firms' TFP.

We now discuss the identification of the coefficients on the individual covariates, Γ_t. In the standard AKM setup with time-invariant firm and worker fixed effects, identification is achieved by using variation in wages for stayers—workers who do not move firms and thus have constant firm and worker fixed effects between two periods. Since we allow firm effects to vary by time, we cannot use stayers to identify the covariates. In fact, in our setting we do not really have stayers in the same sense as the baseline AKM model—every worker faces different firm effects in every period and is thus, in some sense, a switcher. However, we can still identify Γ_t using "common switchers", defined as workers who work in the same firm as each other in two consecutive periods. Denote by C_t the set of common switchers between $t-1$ and t such that $(i,m) \in C_t$ if $f(i,t) = f(m,t)$ and $f(i,t-1) = f(m,t-1)$ where $f(i,t)$ is the firm where worker i is employed in period t. C_t therefore contains workers who remain at the same firm between two years, as well as workers who switch firms together. Consider the difference in labor earnings for two workers, i and m, that work in firm j in period t and k in period $t-1$,

$$\begin{aligned} w_{ijt} - w_{mjt} &= \alpha_i - \alpha_m + (X_{it} - X_{mt})\Gamma_t + \xi_{ijt} - \xi_{mjt} \\ w_{ikt-1} - w_{mkt-1} &= \alpha_i - \alpha_m + (X_{it-1} - X_{mt-1})\Gamma_{t-1} + \xi_{ikt-1} - \xi_{mkt-1} \end{aligned}$$

Subtracting the second equation from the first equation on both sides, we get

$$\Delta w_{it} - \Delta w_{mt} = (X_{it} - X_{mt})\Gamma_t - (X_{it-1} - X_{mt-1})\Gamma_{t-1} + \Delta\xi_{it} - \Delta\xi_{mt}$$

Note that this equation has netted out both the worker and time-varying firm fixed effects. Variation in the wage growth differential for common switchers can therefore help us identify Γ_t for all periods t. [46]

Second, we discuss the identification of the firm-time effects. The firm-time effects for firm j at time

[46] Note that it doesn't matter whether k and j are the same or different firms, so long as workers i and m work together in both periods. As long as they are common switchers, their firm-time fixed effects will cancel and allow us to identify Γ_t.

t and firm k at $t-1$ can be written as:

$$
\begin{aligned}
\psi_{j(i,t)t} =& \mathbb{E}_i\Big[w_{ijt} - \alpha_i + X_{it}\Gamma_t - \xi_{ijt} \;\Big|\; f(i,t) = j\Big] \\
=& \mathbb{E}_i\Big[w_{ijt} - \alpha_i + X_{it}\Gamma_t \;\Big|\; f(i,t) = j\Big] \\
\psi_{k(i,t-1)t-1} =& \mathbb{E}_i\Big[w_{ikt-1} - \alpha_i + X_{it-1}\Gamma_{t-1} - \xi_{ikt-1} \;\Big|\; f(i,t-1) = k\Big] \\
=& \mathbb{E}_i\Big[w_{ikt-1} - \alpha_i + X_{it-1}\Gamma_{t-1} \;\Big|\; f(i,t-1) = k\Big],
\end{aligned}
$$

where the second and fourth line use $\mathbb{E}\left[\xi_{ijt}\right] = 0$. Then, we can write the difference in the firm-by-time fixed effects for individual i that switched from firm k to j as

$$
\psi_{j(i,t)t} - \psi_{k(i,t-1)t-1} = \mathbb{E}_i\Big[w_{ijt} - w_{ikt-1} + X_{it}\Gamma_t - X_{it-1}\Gamma_{t-1}\Big| f(i,t) = j \;\&\; f(i,t-1) = k\Big]
$$

Since Γ_t is identified, and w and X are given by the data, we can identify the firm-time fixed effects using switcher wages and observable characteristics, with a normalization of one firm-time fixed effect. By definition, all workers in our setup are *switchers* since each firm has a different fixed effect in each period.

Finally, we discuss the identification of the time-invariant worker effects. Worker i's fixed effect can be written as:

$$
\begin{aligned}
\alpha_i =& \mathbb{E}_{j(i,t)t}\Big[w_{ijt} - \psi_{j(i,t)t} + X_{it}\Gamma_t - \xi_{ijt}\Big] \\
=& \mathbb{E}_{j(i,t)t}\Big[w_{ijt} - \psi_{j(i,t)t} + X_{it}\Gamma_t\Big].
\end{aligned}
$$

which are functions of data and otherwise identified parameters. Notice that we do not rely on having multiple jobs per worker-year pair for our identification. However, having information on multiple jobs helps us to get better estimates of the worker and firm effects. To see this is the case, assume that individual i worked at firms j and k in period t, then we have:

$$
w_{ijt} - w_{ikt} = \psi_{j(i,t)t} - \psi_{k(i,t)t} + \xi_{ijt} - \xi_{ikt}
$$

so we can get

$$
\begin{aligned}
\psi_{j(i,t)t} - \psi_{k(i,t)t} =& \mathbb{E}\Big[w_{ijt} - w_{ikt} + \xi_{ijt} - \xi_{ikt}\Big| f(i,t) = j \;\&\; f(i,t) = k\Big] \\
=& \mathbb{E}_i\Big[w_{ijt} - w_{ikt}\Big| f(i,t) = j \;\&\; f(i,t) = k\Big]
\end{aligned}
$$

Considering that in our sample more than 50% of workers hold a second job at some point in the sample, including these additional job observations allows for better identification of the firm-by-time fixed effects, increases the number of switchers per firm, and thus mitigates the extent of the limited mobility bias (Andrews *et al.*, 2008).

As is standard in the literature, we can decompose the variance of the log hourly wages as follows

$$
Var\left(w_{ijt}\right) = \underbrace{Var\left(\alpha_i + X_{it}\Gamma_t\right)}_{\text{Worker Component}} + \underbrace{Var\left(\psi_{j(i,t)t}\right)}_{\text{Firm Component}} + \underbrace{2 \times Cov\left(\alpha_i + X_{it}\Gamma_t, \psi_{j(i,t)t}\right)}_{\text{Wage Sorting Component}} + \underbrace{Var\left(\xi_{ijt}\right)}_{\text{Residual}}, \tag{11}
$$

where the first and second components capture the fraction of the variance of the log hourly wages accounted for by heterogeneity across workers and firms, respectively. The third component accounts for the variation in the log hourly wages that can be attributed to the sorting of high-ability workers—as measured by $\alpha_i + X_{it}\Gamma_t$—employed by high-wage firms—as measured by $\psi_{j(i,t)t}$. The results are shown

Table A.7 – Variance Decomposition of Log Hourly Wages Using AKM

	1991-2000	2001-2010	Pooled
Variance of hourly wages $Var\left(w_{ijt}\right)$	0.287	0.315	0.302
Worker heterogeneity $Var\left(\alpha_i + X_{it}\Gamma_t\right)$	0.138	0.155	0.148
Firm heterogeneity $Var\left(\psi_{j(i,t)t}\right)$	0.045	0.052	0.049
Residuals $Var\left(\xi_{ijt}\right)$	0.106	0.110	0.108
Wage sorting $2 \times Cov\left(\alpha_i + X_{it}\Gamma_t, \psi_{j(i,t)t}\right)$	-0.001	-0.003	-0.002
Largest connected set	98.0%	99.0%	99.0%
R^2	62.0%	63.0%	63.0%

Note: Table A.7 shows the decomposition of the variance log hourly wages using the AKM estimates, as in Equation (11), for two time intervals and for the pooled sample. The sorting correlation in the pooled sample is $corr\left(\alpha_i, \psi_{j(i,t)t}\right) = -0.003$. The total number of worker/job/year observations in the pooled sample is 57.3 million, with a total of 4.3 million unique workers, 3.0 million unique firm/years, and 0.45 million unique firms.

in Appendix Table A.7. We find that around 48% of the variance of the log hourly wages is accounted for by workers' observed and unobservable characteristics and 16% is accounted for by firms' time-varying characteristics. Our estimates also show that sorting accounts for almost none of the total variation in hourly wages.

C Alternative Measures of Passthrough

Our empirical approach differs in several different ways to the standard methods used in the rent-sharing literature. In this section, we examine how each of these factors contributes to our results. To do this, we begin with a simple OLS regression of changes in (log) total annual income on changes in (log) firm value added, controlling for individual and firm observables as above. As shown in column 1 of Table A.8, we find significant passthrough from changes in value added to annual income–an elasticity of 0.079 which implies that a one standard deviation change in value added leads to an average change in income of $1,911 US dollars. However, this effect could be due to a number of factors (e.g. the change in annual income could be due to a change in hours worked by the individual, either voluntarily or because of a change in labor demand by the firm).

The change in value added also includes planned shifts in labor demand, which means that a significant portion of the measured elasticity may be the mechanical link between changes in labor captured by changes in value added, and shifts in hours for workers captured in annual income. Column 2 shows the results of regressing changes in annual income on changes in residual value added, which is the predicted residual from a regression of (log) value added on logs of firm capital and labor (measured in full-time equivalents). This strips variation in inputs out of the firm shock and reduces the elasticity to 0.063. However, the change in annual income still combines changes in hourly wage and hours on the worker side.

To decompose how much of the passthrough from shocks to income is due to extensive-margin adjustment in labor demand versus changes in the wage rate, we substitute the dependent variable by changes in the log hourly wage (column 3 of Table A.8). We find that a little more than half of the passthrough to annual income from changes in residual value added is due to changes in the hourly wage, while slightly less than half is due to changes in hours worked (we find similar results when using our more robust measures of firm shocks and wages).

When we additionally eliminate variation in worker ability at the firm level by using our ability-adjusted measure of labor input, a_{jt}, when calculating the value added residual (column 4), passthrough decreases from 0.035 to 0.032. Since passthrough and firm shocks may be related to worker ability, we then add in controls for individual ability (column 5) and find a significant increase in passthrough to 0.042. Finally, column 6 shows the results when we use our fully corrected measure of firm shocks– changes in AKM-adjusted TFP ($\Delta\nu_{jt}$) which unlike the value added residuals from the other regressions is allowed to be correlated with input adjustments. This increases the estimated passthrough to 0.046, which matches the passthrough estimate before we correct for workers mobility, shown in column 5 of Table I. These results indicate first that failing to correct for changes in hours will lead to significant over-estimates of passthrough, while not correcting for worker-level ability and mismeasurement of firm shocks will significantly under-estimate passthrough.

Table A.8 – Comparing Passthrough Under Different Assumptions

	(1) $\Delta w^a_{i,j,t}$	(2) $\Delta w^a_{i,j,t}$	(3) $\Delta w_{i,j,t}$	(4) $\Delta w_{i,j,t}$	(5) $\Delta w_{i,j,t}$	(6) $\Delta w_{i,j,t}$
β	.079***	.063***	.035***	.032***	.042***	.046***
	(.002)	(.002)	(.001)	(.001)	(.002)	(.003)
Firm shock	VA	VAres	VAres	VAres$_{akm}$	VAres$_{akm}$	$\Delta\nu_{jt}$
Individual Ability	N	N	N	N	Y	Y
R^2	.49	.49	.17	.18	.79	.78
Pct Effect	3.4%	2.6%	1.5%	1.6%	2.1%	1.2%
Avg. Effect	$1,911	$1,492	$873	$955	$1,243	$705
Correction	None	Residual	Hours	Quality	Quality	TFP

Table A.8 shows a set of OLS panel regressions controlling for firm and worker characteristics. $w^a_{i,j,t}$ and $w_{i,j,t}$ are log annual income and log hourly wages respectively. Firm shocks are changes in logs of: value added (VA), residualized value added from an OLS regression of value added on firm inputs (VAres), residualized value added using the AKM-adjusted measure of labor (VAres$_{akm}$) and AKM-adjusted total TFP (ν_{jt}). All regressions include firm-level controls (which include, firm age, lagged firm shocks, and firm employment), worker-level controls (which include, a polynomial in age, lagged worker experience, lagged log wage level, lagged tenure in the firm, and gender), and year fixed effects. These results are not selection corrected. $*p < 0.1, **p < 0.05, ***p < 0.01$. Robust standard errors are clustered at the firm-level.

Table A.9 – Passthrough from Firm and Industry TFP shocks to Wages

Dep. Variable	Change in Log Hourly Wages, $\Delta\hat{w}_{i,j,t}$	
	(1)	(2)
Specification:	All	Pos/Neg
$\Delta\nu_{jt}^{f}$	.076***	.058***
	(.004)	(.004)
$\Delta\nu_{jt}^{f} \times \mathbb{I}_{\Delta\nu_{jt}<0}$		.060***
		(.006)
$\Delta\nu_{t}^{k}$	.024***	.00
	(.006)	.015
$\Delta\nu_{t}^{k} \times \mathbb{I}_{\Delta\nu_{t}^{k}<0}$		.046*
		(.023)
$Mills_{it}$	−.209***	−.275***
	(.014)	(.016)
R^2	.78	.78
Obs. (Millions)	6.47	6.47
Monetary Value of a Shock to Firm TFP (US$ 2010)		
$\Delta\nu_{jt}$	$1,041	
$\Delta\nu_{jt} > 0$		$789
$\Delta\nu_{jt} < 0$		$1,595
$\Delta\nu_{t}^{k}$	$67.2	
$\Delta\nu_{t}^{k} > 0$		$0.0
$\Delta\nu_{t}^{k} < 0$		$117

Table A.9 shows a set of OLS panel regressions controlling for firm and worker characteristics. $*p < 0.1, **p < 0.05, ***p < 0.01$. Robust standard errors are clustered at the firm-level.

D Aggregate and Industry Shocks

In this section, we study the impact of aggregate and industry shocks on workers' wages. Separating their effect is important, as there might be general equilibrium effects that confound our passthrough estimates. To separate the effect of aggregate- and industry-level fluctuations in productivity, we follow Carlsson *et al.* (2015) and first regress our firm-level productivity changes on a set of year dummies and calculate the residual change, which is orthogonal to the aggregate cyclical variation in TFP. We then regress those residual changes on a full set of year-industry dummies. The predicted values from this regression give us our measure of industry-level TFP shocks (denoted by $\Delta\nu_{t}^{k}$), where the residuals are our measure of idiosyncratic firm-level changes in TFP (denoted by $\Delta\nu_{jt}^{f}$) which are orthogonal to industry and aggregate fluctuations.

Finally, we regress the change in log hourly wages on these measures of firm- and industry-level productivity shocks. As column (1) of Table A.9 shows, the elasticity of wages to firm-level shocks (after we have stripped out the year and industry components) is essentially the same as in our baseline results (column (1) of Table I), indicating that aggregate shocks play a minor role in our results. Changes in average productivity at the industry-level have a significant impact on workers' wages, although the passthrough is less than a third of the passthrough from idiosyncratic shocks. Furthermore, if we separate positive from negative shocks, we find that only negative industry productivity changes have an impact on workers' wages. The economic impact is small since there is little variation in the industry-level productivity, relative to the aggregate and idiosyncratic variation.

E Simple Model of Labor Market Power

This appendix contains the derivations and results from Section 2.

E.1 A Simple Model of Labor Demand

Consider a profit maximizing firm with production function $y = Af(L)$ where $A > 0$ is the firms' idiosyncratic productivity level. Assume that the production function is such that $f(L) > 0$, $f' > 0, f'' < 0$ and that the firm faces a labor supply curve given by

$$L^s = g(W),$$

where $g(W)$ is twice continuously differentiable with $g(W) > 0$, $g' > 0$. Here W is the real wage per unit of labor. Theorem 1 shows that under very general conditions, an increase in A generates an increase in W, that is, there is positive passthrough from firms' shocks to wages.

Theorem 1. *Under the preceding assumptions on A, W, f, and g, the elasticity of workers' wages for firms' productivity shocks is positive, $\frac{dW}{dA}\frac{A}{W} > 0$, if either of the following two conditions holds: (a) $g'' \leq 0$, or (b) $g'' > 0$ and $d\phi(W)/dW > 0$ with $\phi(W) \equiv g(W)/g'(W)$.*

Proof. The problem of the firm is given by,

$$\pi = \max_L Af(L) - W(L)L \qquad \text{s.t. } L = g(W).$$

We can plug in the labor supply function to rewrite the problem as

$$\pi = \max_W Af(g(W)) - Wg(W).$$

The first order condition with respect to W is given by,

$$\pi'(W) : Af'(g(W))g'(W) - Wg'(W) - g(W) = 0,$$

so we can write

$$\begin{aligned} Af'(g(W))g'(W) &= Wg'(W) + g(W) \\ A &= \frac{Wg'(W) + g(W)}{f'(g(W))g'(W)}, \end{aligned}$$

and in logs

$$\log A = \log\big(Wg'(W) + g(W)\big) - \log\big(f'(g(W))\big) - \log\big(g'(W)\big).$$

Taking derivatives with respect to W we get,

$$d\log A = \frac{g'(W) + Wg''(W) + g'(W)}{Wg'(W) + g(W)} - \frac{f''(g(W))g'(W)}{f'(g(W))} - \frac{g''(W)}{g'(W)}.$$

Hence, we can write

$$\begin{aligned} \frac{d\log A}{d\log W} &= \frac{\frac{g'(W)+Wg''(W)+g'(W)}{Wg'(W)+g(W)} - \frac{f''(g(W))g'(W)}{f'(g(W))} - \frac{g''(W)}{g'(W)}}{\frac{1}{W}} \\ &= W\left(\frac{g'(W) + Wg''(W) + g'(W)}{Wg'(W) + g(W)} - \frac{f''(g(W))g'(W)}{f'(g(W))} - \frac{g''(W)}{g'(W)}\right). \end{aligned} \tag{12}$$

Then, it follows that the elasticity of firms' wages with respect to productivity, $\epsilon_A^w = \frac{d \log W}{d \log A}$, is given by

$$\begin{aligned}
\epsilon_A^w &= \frac{1}{W\left(\frac{g'(W)+Wg''(W)+g'(W)}{Wg'(W)+g(W)} - \frac{f''(g(W))g'(W)}{f'(g(W))} - \frac{g''(W)}{g'(W)}\right)} \\
&= \left[W\left(\frac{2\left(g'\left(W\right)\right)^2 - g\left(W\right)g''\left(W\right)}{\left(\left(Wg'\left(W\right)+g\left(W\right)\right)g'\left(W\right)\right)} - \frac{f''\left(g\left(W\right)\right)g'\left(W\right)}{f'\left(g\left(W\right)\right)}\right)\right]^{-1}. \qquad (13)
\end{aligned}$$

Notice that the second term in the brackets is negative and the denominator of the first term is positive since $f' > 0, f'' < 0$, and $g' > 0$. A sufficient condition for our result to hold is that the numerator of the first term in brackets is positive. If $g''(W) \leq 0$, then this condition is trivially satisfied. If $g'' > 0$, a sufficient condition is that $d\phi(W)/dW > 0$. To see that this is the case, notice that

$$\phi'\left(W\right) = \left[\left(g'\left(W\right)\right)^2 - g\left(W\right)g''\left(W\right)\right] / \left(g'\left(W\right)\right)^2,$$

which implies that

$$\begin{aligned}
\phi'\left(W\right) > 0 &\implies \left(g'\left(W\right)\right)^2 - g\left(W\right)g''\left(W\right) > 0 \\
&\implies 2\left(g'\left(W\right)\right)^2 - g\left(W\right)g''\left(W\right) > 0 \\
&\implies \epsilon_A^w > 0,
\end{aligned}$$

which gives us our result. □

E.2 The Micro-founded Model of Labor Market Power

The framework set up in this section acts as the baseline model for the following sections. Assume that a labor market is populated by N workers and J firms. Each firm operates a simple revenue production function $Y_j = AL_j^\alpha$ where $A_j > 0$ represents firm-specific revenue shifters (such as productivity or demand shocks), and $\alpha \in (0, 1)$ determines returns to scale in labor. Workers can choose to work for any firm j or choose non-employment. Working for firm j provides utility $V_{ij} = \theta \log W_j + \log B_j + \eta_{ij}$ where $W_j > 0$ is the wage paid to workers at firm j, $B_j > 0$ is an exogenous non-pecuniary benefit provided to all workers at the firm, and η_{ij} is the (unobserved to the firm) individual utility gained by worker i at firm j. We will assume that utility is increasing in the (log) wage such that $\theta > 0$. The outside option provides utility $V_{i0} = \theta \log W_0 + \log B_0 + \eta_{j0}$. We assume that η_{ij} follows a type 1 extreme value distribution. This provides the following expression for the share of workers at firm j:

$$S_j = \frac{B_j W_j^\theta}{B_0 W_0^\theta + \sum_{k \in \mathcal{J}} B_k W_k^\theta}$$

where the number of workers at firm j is $L_j = S_j N$ and $I \equiv B_0 W_0^\theta + \sum_k B_k W_k^\theta$ represents a market-level wage index. The labor supply elasticity which arises from this model for firm j is $\epsilon_W^L = \frac{dS_j N}{dW_j} \frac{W_j}{S_j N} = \theta(1 - S_j)$. Firms in this setting will endogenize both the direct effect of wages on labor supply and the indirect effect of wages on the market wage index.

E.2.1 Log-Linear Labor Supply

Suppose the model is as above, but that firms are atomistic such that $S_j \approx 0$ and firms take the market wage index I as exogenous. The labor supply curve is then $g(W) = \tilde{B}_j W_j^\theta$, where $\tilde{B}_j \equiv B_j N/I$ is an exogenous labor supply shifter. To simplify the notation, we dispense with firm subscripts. Firms choose wages to solve the following profit maximization problem:

$$\max_W \{Ag(W)^\alpha - Wg(W)\}$$

which provides the following first order condition:

$$\alpha A g(W)^{\alpha-1} = W \times \left(\frac{1+\epsilon_W^L}{\epsilon_W^L}\right). \tag{14}$$

Since the labor supply curve is log-linear in wages, the labor supply elasticity is a constant: $\epsilon_W^L = \frac{dg(W)}{dW}\frac{W}{g(W)} = \theta$. Plugging in for $g(W)$ and ϵ_W^L and rearranging Equation (14) provides the solution to the firm's optimal wage:

$$W^* = \left(A\alpha \frac{\theta}{1+\theta}\tilde{B}^{\alpha-1}\right)^{\frac{1}{1+\theta(1-\alpha)}}$$

This provides a passthrough elasticity of

$$\epsilon_A^w = \frac{dW}{dA}\frac{A}{W} = \frac{1}{1+\theta(1-\alpha)} \tag{15}$$

which does not depend on firm characteristics and is constant across firms within the labor market.

E.2.2 Adjustment Costs

Suppose the model is as above, with atomistic firms and a log-linear labor supply curve. Further, assume that firms face linear adjustment costs when hiring and firing labor. In particular, the firms must pay a cost of $\phi_1 > 0$ per worker hired, and a cost of $\phi_2 > 0$ per worker fired. The following section shows that the addition of these adjustment costs leads to positive asymmetric passthrough and a passthrough which is decreasing in firm size and productivity. As above we suppress firm subscripts for simplicity of notation. Firms solve the following profit maximization problem:

$$\max_W \left\{Ag(W)^\alpha - Wg(W) - \phi_1(g(W) - L_{-1})I_{L>L_{-1}} - \phi_2(L_{-1} - g(W))I_{L\leq L_{-1}}\right\}$$

where L_{-1} is the firm's previous employment level and $I_{L>L_{-1}}$ is an indicator variable which equals 1 if the firm increases its employment relative to its previous employment level and 0 otherwise. Likewise, $I_{L\leq L_{-1}} = 1$ if the firm decreases employment and is 0 otherwise. We first focus on the first case, where the firm increases its employment such that $I_{L>L_{-1}} = 1$ and $I_{L\leq L_{-1}} = 0$. The first order condition for the firm is:

$$\alpha A g(W)^{\alpha-1} = W\left(\frac{1+\theta}{\theta}\right) + \phi_1$$

It is difficult to solve this equation for W, so instead we can plug in the labor supply curve and solve for A

$$A = \frac{1}{\alpha}\left(\tilde{B}W^\theta\right)^{1-\alpha}\left(\frac{1+\theta}{\theta}W + \phi_1\right). \tag{16}$$

We are interested in the passthrough elasticity: $\epsilon_A^w = \frac{dW}{dA}\frac{A}{W}$, but it is easier to derive $\frac{1}{\epsilon_A^w} = \frac{dA}{dW}\frac{W}{A}$. We can plug in the expression of A from the previous step and get the following:

$$\frac{1}{\epsilon_A^w} = \frac{dA}{dW}\frac{W}{A} = \frac{W(1+\theta)}{W(1+\theta)+\phi_1\theta} + \theta(1-\alpha).$$

Since this equation is continuous and monotone in wages, we can invert it to obtain the passthrough elasticity for positive changes in employment. Since labor is strictly increasing in productivity, this also means that this is the passthrough elasticity for positive changes in productivity:

$$\epsilon^w_{A+} = \frac{1}{\frac{W_j(1+\theta)}{W_j(1+\theta)+\phi_1\theta} + \theta(1-\alpha)} \text{ if } \Delta A_j > 0, \tag{17}$$

A similar procedure gives us the passthrough elasticity for negative changes in productivity:

$$\epsilon^w_{A-} = \frac{1}{\frac{W_j(1+\theta)}{W_j(1+\theta)-\phi_2\theta} + \theta(1-\alpha)} \text{ if } \Delta A_j < 0. \tag{18}$$

Note that when $\phi_1 = \phi_2 = 0$ both of these elasticities collapse back to the constant and symmetric elasticity from the log-linear case, i.e.: $\epsilon^w_{A+} = \epsilon^w_{A-} = \frac{1}{1+\theta(1-\alpha)}$. If the adjustment costs are not zero, then equations (17) and (18) show that passthrough will depend on wages and thus firm productivity. In particular, we know that for positive hiring and firing costs, we have $\epsilon^w_{A+} > \frac{1}{1+\theta(1-\alpha)} > \epsilon^w_{A-}$, which implies positive asymmetric passthrough for any positive hiring and firing costs.

We then ask whether the passthrough elasticities are increasing or decreasing in the magnitude of the costs. To answer this question, we first consider the hiring cost case (ϵ^w_{A+}):

$$\frac{d\epsilon^w_{A+}}{d\phi_1} = \frac{\theta(\theta+1)\left(W - \phi_1 \frac{dW}{d\phi_1}\right)}{\left((1-\alpha)\theta^2\phi_1 + (\theta+1)((1-\alpha)\theta+1)W\right)^2}$$

where we have taken into account that the optimal wage is an implicit function of the hiring cost parameter. In order to determine the sign of this expression, we need to solve for $\frac{dW}{d\phi_1}$. To do this, note that from the first order conditions (Equation (16)) we know that the wage is an endogenous variable which is a function of exogenous variables $(A, \tilde{B})$ and parameters (α, θ, ϕ_1). Taking derivatives with respect to ϕ_1 on both sides of Equation (16) provides

$$0 = \frac{\tilde{B}^{1-\alpha} W^{\theta(1-\alpha)-1}\left(\frac{dW}{d\phi_1}\left((\alpha-1)\theta^2\phi_1 + (\theta+1)((\alpha-1)\theta-1)W\right) - \theta W\right)}{\alpha\theta}.$$

Solving for $\frac{dW}{d\phi_1}$ gives us

$$\frac{dW}{d\phi_1} = -\frac{\theta W}{(1-\alpha)\theta^2\phi_1 + W(\theta+1)(1+\theta(1-\alpha))} < 0.$$

Thus, equilibrium wages are decreasing in hiring costs. This is intuitive: the more employment increases, the more wages increase. Since increases in hiring costs reduce the equilibrium employment of the firm, we will see lower wages as hiring costs increase. This also means that the passthrough elasticity for positive productivity shocks is strictly increasing in the hiring cost, i.e.: $\frac{d\epsilon^w_{A+}}{d\phi_1} > 0$. A similar exercise shows that the passthrough of negative shocks is strictly decreasing in firing costs, i.e.: $\frac{d\epsilon^w_{A-}}{d\phi_2} < 0$. This confirms the above intuition that passthrough in this model will be positive and positive asymmetric for any linear hiring or firing costs. However note that the passthrough elasticity itself is also *decreasing* in log productivity $\left(\frac{d\epsilon^w_{A+}}{dlogA} < 0\right)$, meaning that while passthrough for individuals firms will be positive asymmetric, larger and more productive firms will tend to have less passthrough of both positive and negative shocks than smaller firms. To confirm this, observe that

$$\frac{d\epsilon^w_{A+}}{d\log A} = \frac{\theta(\theta+1)W\phi_1(\theta\phi_1 + (1+\theta)W)}{\left((\alpha-1)\theta^2\phi_1 + (\theta+1)W((\alpha-1)\theta-1)\right)^3} < 0$$

which is negative since $\alpha < 1$.

E.2.3 Labor Market Power

Here we return to the general logit demand model in Appendix E.2 above with non-atomistic firms. This framework allows for competitive interaction between firms with varying degrees of labor market power. We include the firm subscript notation in order to differentiate between the wage and labor share of the firm (j) from the outside option (0). The labor supply function for a firm in this market is then

$$g(W_j) = S_j N = \frac{B_j W_j^\theta}{B_0 W_0^\theta + \sum_{k\in\mathcal{J}} B_k W_k^\theta} N$$

where the firm interacts strategically with other firms by endogenizing the effect of wage changes on the market wage index. Taking derivatives of S_j with respect to the wage gives us:

$$\frac{dS_j}{dW_j} = \theta(1-S_j)\frac{S_j}{W_j}$$

which provides the following expression for the labor supply elasticity:

$$\begin{aligned}\epsilon_W^L = \frac{dg(W_j)}{dW_j}\frac{W_j}{g(W_j)} &= \frac{dS_j}{dW_j}N\frac{W_j}{L_j}\\ &= \theta(1-S_j).\end{aligned}$$

The firm's problem is the same as in appendix E.2.1, giving the same first order condition of

$$\alpha A_j g(W_j)^{\alpha-1} = W_j \times \left(\frac{1+\epsilon_W^L}{\epsilon_W^L}\right). \tag{19}$$

Note that in this case, the share and labor supply elasticity are all implicit functions of A_j via the wage (i.e.: $S_j(W_j(A_j))$ and $\epsilon_W^L(W_j(A_j))$). We can take the derivative of this expression w.r.t. A_j on both sides to obtain:

$$L^{\alpha-1}\alpha S_j^{\alpha-2}\left(S_j + \frac{dW_j}{dA_j}A_j(\alpha-1)\frac{dS_j}{dW_j}\right) = \frac{dW_j}{dA_j}\left(1 + \frac{\epsilon_W^L - W_j\frac{d\epsilon_W^L}{dW_j}}{\left(\epsilon_W^L\right)^2}\right).$$

Solving for $\frac{dW_j}{dA_j}$ and multiplying by $\frac{A_j}{W_j}$, we obtain the passthrough elasticity:

$$\epsilon_A^w \equiv \frac{dW_j}{dA_j}\frac{A_j}{W_j} = \frac{A_j}{W_j\left(\frac{N^{1-\alpha}S_j^{1-\alpha}\left(\epsilon_W^L + \left(\epsilon_W^L\right)^2 - W_j\frac{d\epsilon_W^L}{dW_j}\right)}{\alpha\left(\epsilon_W^L\right)^2} + A_j(1-\alpha)\frac{dS_j}{dW_j}\frac{1}{S_j}\right)}.$$

By noting that $\frac{d\epsilon_W^L}{dW_j} = -\theta\frac{dS_j}{dW_j}$, using equation (19) to substitute in for A_j, and plugging in the values for $\frac{dS_j}{dW_j}$ and ϵ_W^L, we can obtain an expression for the passthrough elasticity in terms of parameters and the firm's labor market share:

$$\epsilon_A^w = \frac{1+\theta(1-S_j)}{1+\theta(1+(1+\theta(1-S_j))(1-\alpha)(1-S_j))} > 0.$$

Since $S_j \in (0,1)$, we know that the passthrough elasticity in this model is positive. The next question is whether or not the passthrough elasticity is increasing or decreasing in log productivity, A_j. We can take the derivative of the elasticity with respect to $\log A_j$ which, after the same substitution process as above, leads to the following expression:

$$\frac{d\epsilon^w_A}{d\log A_j} = \frac{\theta^2(S_j-1)S_j(\theta(S_j-1)-1)\left(\alpha(\theta(1-S_j)+1)^2-\theta\left(\theta(1-S_j)^2-2S_j+1\right)\right)}{\left(\theta\left(\alpha-(1-\alpha)\theta(1-S_j)^2+S_j(1-\alpha)-2\right)-1\right)^3}.$$

The sign of this expression depends on both labor market parameters and firm characteristics. In particular, $\frac{d\epsilon^w_A}{d\log A_j} > 0$ if and only if $0 < \alpha < \frac{\theta}{1+\theta}$ and $0 < S_j < 1 + \frac{1}{\theta} - \sqrt{\frac{1+\theta}{(1-\alpha)\theta^2}}$. This means that in a labor market with very elastic labor supply (θ sufficiently high relative to α), there is a size cutoff, S^*, where larger firms pass negative productivity shocks on to wages more than positive shocks (negative asymmetric passthrough) while smaller firms pass positive shocks on to wages more than negative shocks (positive asymmetric passthrough). Since firm share is itself strictly increasing in productivity, this implies that the passthrough curve (the relationship between log wages and log productivity) is s-shaped—convex for low A_j and concave for high A_j. The cutoff between "small firm" and "large firm" in this context (the inflection point in the curve) is determined by the ratio of the utility value of log wages θ to the returns to scale parameter α. In markets with fairly inelastic labor ($\theta \to 0$) or close to constant returns to scale ($\alpha \to 1$), that size cutoff goes to zero and all firms will exhibit negative asymmetric passthrough. For example, in the simple case where $\alpha = \theta = 1$, passthrough will be negative asymmetric and decreasing in size/productivity for all firms.

E.2.4 Other Labor Supply Curves

Finally, suppose the labor supply curve is not log-linear and takes the form $g(W) = B_j W_j^\theta + C_j$ where $C_j < 0$ represents the (negative) amenities or dis-utility experienced by those employed at firm j. As before we assume B_j, W_j, and θ are all positive and suppress the firm subscripts. This labor supply curve provides the following labor supply elasticity:

$$\epsilon^L_W = \frac{\theta B W^\theta}{BW^\theta + C}.$$

The firm's problem is the same as above. Taking the first order condition (see Equation (14)), and plugging in the values for $g(W)$ and ϵ^L_W, we get

$$BW^\theta\left(-\frac{\alpha A\theta\left(BW^\theta+C\right)^{\alpha-1}}{W}+\theta+1\right)+C=0. \tag{20}$$

Solving for A gives us

$$A = \frac{W^{1-\theta}\left((\theta+1)BW^\theta+C\right)\left(BW^\theta+C\right)^{1-\alpha}}{\alpha B\theta}. \tag{21}$$

To obtain the passthrough elasticity, we take derivatives with respect to A on both sides of Equation (20), solve for $\frac{dW}{dA}$ and multiply by $\frac{A}{W}$. This gives us

$$\epsilon^w_A = \frac{dW}{dA}\frac{A}{W} = -\frac{\alpha A\left(BW^\theta+C\right)^{\alpha+1}}{\alpha A\left(BW^\theta+C\right)^\alpha\left(B(\alpha\theta-1)W^\theta+C(\theta-1)\right)-(\theta+1)W\left(BW^\theta+C\right)^2}.$$

We can simplify this by plugging in the expression for A in Equation (21). The passthrough elasticity is then

$$\epsilon^w_A = \frac{1}{1+\theta(1-\alpha)-\theta\left(\frac{(1-\alpha)C}{BW^\theta+C}+\frac{C}{(1+\theta)BW^\theta+C}\right)} > 0$$

which, as expected, is positive. Taking derivatives with respect to log productivity gives

$$\frac{d\epsilon^w_A}{d\log A_j} = -\frac{BC\theta^2W^\theta\left(BW^\theta+C\right)\left(B(\theta+1)W^\theta+C\right)\Theta}{\left(B^2(\theta+1)((\alpha-1)\theta-1)W^{2\theta}+BC((\alpha-1)\theta-2)W^\theta+C^2(\theta-1)\right)^3}$$

with $\Theta \equiv \left(C^2(\alpha-\theta-2)+B^2(\theta+1)((\alpha-1)\theta+\alpha-2)W^{2\theta}+2(\alpha-2)BC(\theta+1)W^{\theta}\right)$ which is always positive under the above assumptions and as long as $B_jW_j^{\theta}+C_j>0$. Thus the relationship between log wages and log productivity is convex and passthrough in this model is positive asymmetric.

F Additional Explanations

F.1 Financial Constraints

Several studies have suggested that financial constraints might account for the positive passthrough from firm shocks to wages. The starting point is a basic theory of the firm which suggests that the intrinsic role of entrepreneurs is to provide insurance to workers: firms are more able to hedge against risk, thus allowing them to insulate workers from shocks. However, the ability of a firm to insure its workers against market risk will depend on that firm's ability to insure itself. For example, an aggregate shock that tightens a firm's borrowing constraint reduces its ability to insure its workers against idiosyncratic productivity shocks, more so for young or small firms which are potentially more constrained than old and large firms.

Intuitively, firms that are more financially constrained should be more likely to pass negative productivity shocks on to their workers, while less financially constrained firms will be better able to insure workers against such shocks. Larger shocks are also more likely to push a firm up against its constraints than smaller shocks, so we should see significantly more passthrough for larger (negative) shocks than for positive shocks. We test these implications directly in the following sections.

In an important contribution, Michelacci and Quadrini (2009) study the relationship between financial constraints and firm wage policies in a model in which firms can commit to long-term wage contracts. Two key predictions arise from their model: first, future firm growth is negatively correlated with the wages of new hires, and second, wage growth for incumbent workers (stayers) is positively correlated with firm growth. In their model, firms find it profitable to commit to back-loaded wage profiles since at least part of the capital accumulated by the firm is embodied in the worker in the form of recruiting costs or firm-specific human capital. Hence, firms "borrow" from their workers to increase their short-run growth rate. Workers, however, cannot commit to stay in the firm, and therefore, wages do not decrease—the worker can always leave and obtain the market rate. Thus, one should expect zero passthrough from negative growth to wages for stayers, which is somewhat at odds with our main results.

F.2 Search Frictions

Imperfections in the labor market originating from search frictions may also rationalize positive passthrough from firm productivity shocks to wages. Consider for instance a search and matching model in which the value of the match is split between firms and workers using a sequential auction protocol, as in Postel-Vinay and Turon (2010) or Lise, Meghir and Robin (2016). Workers are heterogeneous in their fixed type p, whereas firms differ in their productivity ε, which varies over time. We denote the surplus generated by the firm-worker match by $S(\varepsilon,p)$ and the worker's valuation of the match by $V(\varepsilon,p)$. The worker's wage contract is denoted by $\omega(r,p)$, which depends on the worker type p, the worker's negotiation baseline r, and is defined as follows

$$\omega=\omega(r,p)\Leftrightarrow V(\phi,p)=V_0(p)+S(r,p)\Leftrightarrow \Pi(\varepsilon,\omega,p)=S(\varepsilon,p)-S(r,p),$$

where $V_0(p)$ is the worker's lifetime value of unemployment, and Π denotes firm profits.

Suppose the output from a match takes the form: $y_t=p\varepsilon$, and consider the case in which the firm gets a shock that moves its productivity to ε' such that $\varepsilon_{min}\leq\varepsilon'<r$, where ε_{min} represents the lowest productivity level at which the match generates a positive surplus. The first part of the inequality ensures that the match is still viable, so $S(\varepsilon',p)>0$ and workers and firms benefit from maintaining this match. The second inequality, however, indicates that profits are negative at the current wage schedule $\omega(r,p)$, since $S(\varepsilon', p) - S(r, p) < 0$. Firms are thus better off firing the worker rather than maintaining the match at the original wage level, and therefore, have a credible threat to force a renegotiation of the wage contract. As long as $V(\varepsilon', p)$ is greater than the value of unemployment, workers will be willing to accept a lower wage rate at $\omega(\varepsilon', p)$. Hence, the passthrough elasticity of workers' wages with respect to firms' idiosyncratic productivity is given by

$$\frac{dw}{da}\frac{A}{w} = \frac{\omega(\varepsilon', p) - \omega(\varepsilon, p)}{(\varepsilon' - \varepsilon)\omega(\varepsilon, p)}\varepsilon,$$

which is greater than 0, but less than 1, i.e., the firm provides some insurance to workers.

Two important implications of the model are worth mentioning. First, without further assumptions, the model will have difficulty producing the passthrough of positive productivity shocks that we find in the data. To see this, consider a firm that receives a positive change in productivity, such that $\varepsilon' > \varepsilon$. In this case, firms do not have any incentive to renegotiate wages, while the workers cannot force wage renegotiation and obtain rents from this positive shock unless they receive a competing outside offer at the same time, or an increase in the value of the option of looking for another job.

Second, we should expect size dependence in the passthrough of negative shocks: small changes in productivity that do not trigger a renegotiation should have almost no impact on the wage rate, whereas large productivity shocks should command a higher passthrough. To see this, consider a small negative productivity shock such that $r < \varepsilon' < \varepsilon$ so that the shock is above the worker's negotiation threshold. In this case, the negative shock to productivity does not generate a decline in the worker's wages, as the firm is not able to make a credible threat of firing the worker and forcing the a wage renegotiation. Note that, like in the labor market power model, the data generated from this model will also suffer from the selection bias problem we find. Large negative shocks will induce separation, while smaller and positive shocks will not. This last prediction is consistent with our results that show that the largest negative firm shocks have the greatest effect on worker mobility out of the firm.